Evaluating Policy Institutions*

–150 Years of US Monetary Policy–

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Abstract

Given a loss function and a set of policy objectives, how should we evaluate and compare the performances of policy institutions? In this work, we show that it is possible to evaluate policy makers with minimal assumptions on the underlying economic model. The Distance to Minimum Loss —the component of the loss that a policy institution can be held accountable for—, can be computed from well known and estimable sufficient statistics: the impulse responses to policy and non-policy shocks. We use our methodology to evaluate US monetary policy since 1879. We find no material improvement in performance over the first 100 years, and it is only in the last 30 years that we estimate large and uniform improvements in the conduct of monetary policy.

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1 Introduction

How should we evaluate and compare the performance of policy institutions? How should we evaluate and compare policy makers after their term in office? These questions are of central importance to the good functioning of democratic and accountable institutions, but there is little consensus on a method for evaluating and comparing performance.

A naive approach would consist in measuring performance based on realized macroeconomic outcomes; on the realized value of some loss function. For instance, we could assess a central banker based on average inflation and unemployment outcomes over her term. Unfortunately, that approach suffers from numerous confounding problems, as many factors are outside policy makers' control but affect performance: (i) different policy makers may face different initial conditions upon beginning their term, e.g. a central banker can inherit a strong or weak economy from her predecessor, and this will influence realized outcomes, (ii) different policy makers may face different economic disturbances, e.g., a central banker may experience a financial crisis or an energy price shock that will affect her ability to stabilize inflation and unemployment, and (iii) different policy makers may live in different economies —different environments—, e.g., a steeper or flatter Phillips curve will affect a central banker's ability to control inflation.

To avoid these confounders, an ideal approach should take into account the underlying model of the economy in order to derive an optimal rule; a policy rule that delivers the minimum loss possible *given* the environment faced by a policy maker. A policy maker is best performing when she follows such optimal rule, and we can rank policy makers based on their *distance to minimum loss* (DML) —the distance between their realized loss and the minimum loss possible given the environment—. Better performing policy makers will feature smaller distances to minimum loss.

A structural approach will then consist in specifying and estimating a structural model over the policy maker's term, and use that model to evaluate policy makers and institutions. A risk with a model-based approach however is model mis-specification: if the model is mis-specified, the estimated DML can be inaccurate and lead to erroneous policy evaluation.

In this paper, we show that it is possible to measure the DML with minimal assumptions on the underlying economic model. Specifically, for a large class of linear forward looking macro models and quadratic loss functions, it is possible to measure the DML from well known and estimable sufficient statistics: the impulse responses (IRs) to policy and non-policy shocks.

To measure the DML with sufficient statistics, the key difficulty is to measure the minimum feasible loss: to characterize the optimal policy rule without having to rely on a specific underlying model. We achieve this thanks to two new results. First, an identification result:

knowledge of the optimal reaction to structural shocks alone is sufficient to characterize the optimal policy rule, that is to construct a policy rule that minimizes the loss function given the environment. Second, a sufficient statistics result: the impulse responses to policy and non-policy shocks are sufficient to characterize the effects and optimal reaction to structural shocks.

Taken together, these results imply that the optimal reaction function can be characterized from impulse responses to shocks, and in fact from simple regressions in "impulse response space": regressions of the impulse responses to non-policy shocks on the impulse responses to policy shocks. Each regression coefficient measures by how much more or less the policy maker should have responded to a given non-policy shock, and this *optimal reaction adjustment* (ORA) can be used to measure the distance to minimum loss conditional on a specific type of non-policy shock. Overall policy performance —the total distance to minimum loss— can then be computed by aggregating these distances across the different shocks.

In a dynamic setting computing the total DML requires identifying all policy and non-policy news shocks at all possible horizons. While this data requirement is unlikely to be met in practice, we show how subset statistics, which only use a subset of the different types of shocks, can be used to evaluate policy makers. Intuitively, this property stems from our characterization of the optimal rule as a set of optimal reaction coefficients to different types of shocks. Since each type of shock can be studied separately from the others, we can split the optimal policy problem into separate problems, and evaluate policy makers separately for each type of shock.

We apply our methodology to study the performance of US monetary policy over the past 150 years and revisit many important questions regarding the conduct of monetary policy: (i) Did the founding of the Federal Reserve in 1913 led to superior macro outcomes than during the passive Gold standard period (e.g., Bordo and Kydland, 1995)? (ii) While many people would agree that monetary policy was superior during the 2007-2009 financial crisis than during the 1929-1933 financial crisis (e.g., Wheelock et al., 2010), can we confirm and quantify this improvement? In other words, did Bernanke fulfill his promise to Milton Friedman when he said that the Fed "won't do it again", i.e., won't repeat the mistakes of the Great Depression (Bernanke, 2002)? (iii) More generally, did monetary policy improve since the Great Depression? Is the Great Moderation post Volcker a sign of good policy or simply the outcome of good luck? (e.g., Clarida, Galí and Gertler, 2000; Galí and Gambetti, 2009)?

To assess and compare monetary policy performance across historical periods, we evaluate how monetary policy responded to five types of non-policy shocks: (i) financial shocks, (ii) government spending shocks, (iii) energy price shocks, (iv) inflation expectation shocks and

(v) productivity shocks, and we evaluate US monetary policy over four distinct periods: (a) 1879-1912 covering the Gold standard period until the founding of the Federal Reserve, (b) 1913-1941 covering the early Fed years to the US entering World War II, (c) 1954-1984 covering the post World War II period until the beginning of the Great Moderation, and (d) 1990-2019 covering the Great Moderation period, the financial crisis and up to the COVID crisis. In each case, we leverage on a large empirical literature on structural shocks identification to identify banking panics (Reinhart and Rogoff, 2009), energy price shocks (Hamilton, 2003), government spending shocks (Ramey and Zubairy, 2018), TFP shocks (Gali, 1999), inflation expectation shocks (Leduc, Sill and Stark, 2007) and monetary shocks (Friedman and Schwartz, 1963; Romer and Romer, 1989, 2004*b*; Gürkaynak, Sack and Swanson, 2005). The identification of monetary shocks is less developed for the Gold Standard period, and we propose a new identification strategy based on large gold mine discoveries.

Given a loss function that places equal weight on inflation and unemployment, our main results are as follows: (i) we estimate large and uniform improvements in the conduct of monetary policy, but *only* in the last 30 years, (ii) we cannot reject that the Fed's reaction to recent financial shocks (notably the 2007-2008 financial crisis) was appropriate, in contrast to the "highly" sub-optimal reaction of the Fed during the Great Depression, (iii) despite much larger realized losses in the 1920s-1930s, the performance of the early Fed is no worse than the performance of the passive Gold Standard, and (iv) the Fed's reaction function during the 1960s-1970s is almost as sub-optimal as the reaction function of the early Fed.

Related literature An early contribution is Fair (1978) who highlights the distortions stemming from different initial conditions and economic environments. His solution was to adopt optimal control methods to compare policy makers through the lens of a fully specified model. Modern versions of this approach include (e.g. Galı, López-Salido and Vallés, 2003; Gali and Gertler, 2007; Blanchard and Galí, 2007). Unfortunately, specifying the correct model for (i) the policy rule and (ii) the macroeconomic non-policy block is a difficult task (e.g., Svensson, 2003; Mishkin, 2010). A less structural approach has studied monetary performance through the lens of estimated policy rules —requiring only the specification of a policy rule—.[1] In particular, a number of studies compared the Fed in the pre- and post-Volcker periods by assessing whether the Taylor principle was satisfied. However, beyond the Taylor principle, that approach can say little about the optimality of reaction functions, and thus can only provide a coarse evaluation of reaction functions.

In the context of fiscal policy Blinder and Watson (2016) improve on the naive approach

[1]See Taylor (1999); Clarida, Galí and Gertler (2000); Orphanides (2003); Coibion and Gorodnichenko (2011) for policy rules estimates.

of policy evaluation —measuring performance based on unconditional realized outcomes— by *projecting out* specific macro shocks, i.e., by trying to control for good (or bad) luck. In contrast, our approach *projects on* the space spanned by specific non-policy shocks and study performance in that space.

Closer to our work, the literature has proposed reduced-form methods to study policy rule counterfactuals (e.g., Sims and Zha, 2006; Bernanke et al., 1997; Leeper and Zha, 2003), though these approaches are not fully robust to the Lucas critique. Instead, our approach builds on recent work showing that robustness to the Lucas critique is possible in a large class of macroeconomic models (McKay and Wolf, 2023): When the coefficients of the non-policy block are independent of the coefficients of the policy block, it is possible to reproduce any policy rule counterfactual with an appropriate combination of policy news shocks at different horizons. Our work exploits a little studied class of policy rule counterfactuals —counterfactual reactions to non-policy shocks—, which have appealing properties: (i) the class is sufficient to characterize the optimal reaction function, (ii) the class allows to split the optimal policy problem into computationally simple separate problems, allowing to evaluate policy makers under subset identification, and (iii) each sub-problem has an economic interpretation; allowing to better understand the sources of sub-optimal policy decisions, for instance the types of shocks that policy makers could have been handled better. This last property allows us to relate to a large literature on previous policy misses.

In fact, our historical evaluation of monetary policy relates to monumental narrative studies of monetary policy, from Friedman and Schwartz (1963) seminal work to the more recent work of Meltzer (2009). Our study builds on this narrative evidence in that much our shock identification draws on the narrative identification approach pioneered by Friedman and Schwartz (1963) and Romer and Romer (1989). While our historical study is necessarily less thorough than these historical accounts, we show that it is possible to use narrative *qualitative* accounts to make objective and *quantitative* statements about historical policy performance.

Last, our paper relates to the sufficient statistics approach for macro policy proposed in Barnichon and Mesters (2023). Different from our focus on reaction function evaluation, Barnichon and Mesters (2023) focus on the time t optimal policy problem —how to set the policy path today given the state of the economy—, instead of the unconditional policy problem that we consider here —how to set up the policy rule to minimize the unconditional loss—. Barnichon and Mesters (2023) show that the characterization of the optimal targeting policy rule can be reduced to the estimation of two sufficient statistics (i) the impulse responses of the policy objectives to policy shocks, and (ii) oracle forecasts for the policy objectives conditional on some baseline policy rule. McKay and Wolf (2022, 2023) offer a similar result in the context of unconditional loss minimization. This paper uses a different set of sufficient statistics—policy *and* non-policy shocks—, allowing to by-pass the need for conditional forecasts data as well as providing an economic interpretation for the sources of optimization failures, as discussed above.

2 Illustrative example

Before formally describing our general framework, we first illustrate how it is possible to evaluate and compare policy makers without having access to the underlying economic model nor the policy rule. To illustrate the method, we take a baseline New Keynesian (NK) model, which allows us to highlight the main mechanisms of our approach and relate to the broad NK literature (e.g. Galí, 2015).

The log-linearized Phillips curve and intertemporal (IS) curve of the baseline New-Keynesian model are given by

$$\pi_t = \beta \mathbb{E}_t \pi_{t+1} + \kappa x_t + \sigma_\xi \xi_t \ , \tag{1}$$

$$x_t = \mathbb{E}_t x_{t+1} - \frac{1}{\sigma}(i_t - \mathrm{E}_t \pi_{t+1}) \ , \tag{2}$$

with π_t the inflation gap, x_t the output gap, i_t the nominal interest rate set by the central bank and ξ_t a cost-push shock.[2] The parameters are collected in $\theta = (\kappa, \sigma, \sigma_\xi)'$. We can think of θ as capturing the economic "environment".

The policy maker sets the interest rate following the rule

$$i_t = \phi_\pi \pi_t + \sigma_\epsilon \epsilon_t \ , \tag{3}$$

where ϵ_t is a policy shock and $\phi = (\phi_\pi, \sigma_\epsilon)$ is a vector of policy parameters. We impose that the structural shocks ξ_t and ϵ_t are serially and mutually uncorrelated with mean zero and unit variance.[3]

For $\phi_\pi > 1$ we can solve the model and express the endogenous variables $Y_t = (\pi_t, x_t)'$ as functions of the exogenous shocks.

$$\begin{aligned} Y_t &= \Gamma \xi_t + \mathcal{R} \epsilon_t \ , \quad \text{with} \\ \Gamma &= \Gamma(\phi, \theta) = \sigma_\xi \begin{bmatrix} \frac{1}{1+\kappa\phi_\pi/\sigma} \\ \frac{-\phi_\pi/\sigma}{1+\kappa\phi_\pi/\sigma} \end{bmatrix} \quad \text{and} \quad \mathcal{R} = \mathcal{R}(\phi, \theta) = \sigma_\epsilon \begin{bmatrix} \frac{-\kappa/\sigma}{1+\kappa\phi_\pi/\sigma} \\ \frac{-1/\sigma}{1+\kappa\phi_\pi/\sigma} \end{bmatrix} . \end{aligned} \tag{4}$$

[2] In this work, we focus on stationary environments, in which variables evolve around their steady-state. This excludes drifting policy objectives and cases of systematically too low or too high policy instruments; for instance cases of hyper-inflation or unsustainable debt.

[3] This assumption is without loss of generality, and the generic treatment of section 3 accommodates more general (notably serially correlated) exogenous processes.

The vectors Γ and $\mathcal{R}$ capture the impulse responses of the policy objectives to the structural shocks. Note that Γ and $\mathcal{R}$ depend on the environment parameters θ and the policy rule parameters ϕ, which include the standard deviations of the structural shocks.

Evaluating policy makers requires taking a stance on a performance metric. To that effect, we consider the unconditional loss function

$$\mathcal{L}(\phi;\theta) = \mathbb{E}Y_t'Y_t \ , \qquad \text{which using (4) becomes} \ \ \mathcal{L}(\phi;\theta) = \Gamma'\Gamma + \mathcal{R}'\mathcal{R} \ . \tag{5}$$

Given this loss function, an "optimal reaction function" is defined as any ϕ that minimizes $\mathcal{L}(\phi;\theta)$ given the underlying structure of the economy, i.e., given equations (1)-(3). An optimal reaction function can thus be seen as a policy rule that best stabilizes (minimizes the sum-of-squares) the impulse responses to shocks.

In this example the optimal reaction function is unique and given by $\phi^{\text{opt}} = (\phi_\pi^{\text{opt}}, \sigma_\epsilon^{\text{opt}})' = (\kappa\sigma, 0)'$ (e.g. Galí, 2015). First, exogenous policy changes are not optimal, and an optimal policy features no policy shocks ($\sigma_\epsilon^{\text{opt}} = 0$, which implies $\mathcal{R} = 0$). Second, the optimal reaction coefficient ϕ_π^{opt} is the coefficient that minimizes the effects of cost-push shocks, i.e., that best stabilizes Γ. The minimum loss is then given by $\mathcal{L}^{\text{opt}} = \Gamma^{\text{opt}\prime}\Gamma^{\text{opt}}$, with $\Gamma^{\text{opt}} \equiv \Gamma(\phi^{\text{opt}}, \theta)$: the minimal effect of cost-push shocks that a policy maker can achieve on average given the environment θ.

A naive approach to policy evaluation

Consider a policy maker with reaction function ϕ^0 during her term and associated loss $\mathcal{L}^0 = \mathcal{L}(\phi^0;\theta)$. How should we evaluate that policy maker?

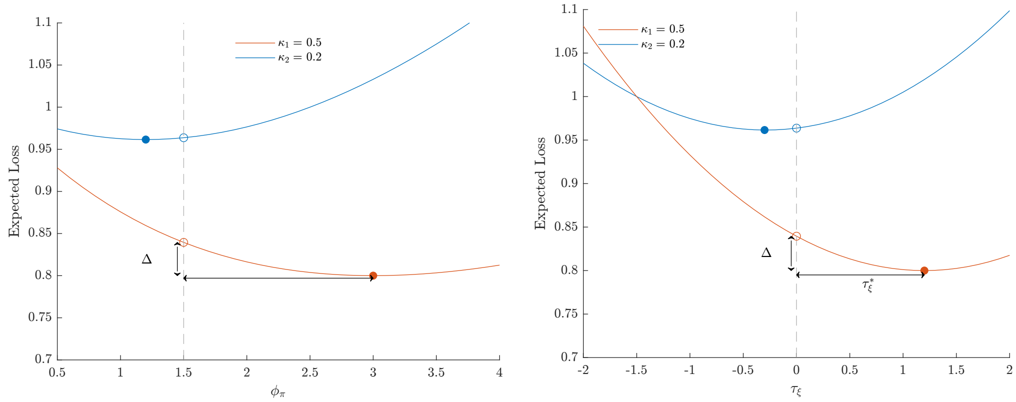
A naive approach would consist in comparing realized losses. Specifically, (i) compute the average loss during a policy maker's term, which provides an estimate of the loss $\mathcal{L}^0$, and (ii) evaluate and rank policy makers based on that estimate. Policy makers with higher average loss would then be deemed less performant.

Unfortunately, the parameter vector θ that describes the economic environment is outside the control of the policy maker and acts as a confounder by influencing the impulse responses to shocks and thus the loss, see (4) and (5).

To give a concrete example of how the economic environment can distort policy evaluation, consider two policy makers —Red and Blue— following the same rule $\phi_\pi = 1.5$ but operating in different environments: one with a steeper Phillips curve ($\kappa = 0.5$) and the other with a flatter Phillips curve ($\kappa = 0.2$). Figure 1a plots the expected loss function as a function of the parameter ϕ_π for these two policy makers.[4]

[4]As illustrative calibration, we take $\beta = .99$, $\sigma = 6$, $\sigma_\epsilon = 0$ and $\sigma_\xi = 1$.

Figure 1: Loss based Policy Evaluation



(a) Naive loss-based evaluation (b) Using auxiliary loss to measure Δ

The optimal rule ϕ_π^{opt} is indicated by the filled dots. The empty dots indicated the policy maker's policy rule ϕ_π^0. The left panel depicts the original loss function $\mathcal{L}(\phi;\theta)$ with $\phi = (\phi_\pi, 0)$ and traces the loss as a function of ϕ_π. The right panel depicts the auxiliary loss function $\mathsf{L}(\tau;\phi^0,\theta)$ with $\tau = (\tau_\xi, 0)$ and traces the loss as a function of τ_ξ. Note how the levels of both loss functions are identical in two points: (i) at the baseline rule ϕ^0 and (ii) at the optimum.

The expected loss under Red —the policy maker under the steep Phillips curve— is lower than under Blue —the policy maker under the flat Phillips curve—: the empty dot is lower for Red than for Blue. A naive approach to policy evaluation would thus conclude that Red is a better policy maker than Blue. However, it's the exact opposite: in this example, Red is further away from the optimal reaction function (filled dot) than Blue. In other words, Red performs less well than Blue. The reason for these different conclusions is the underlying environment: in the steep Phillips curve world of Red, it is *easier* to achieve a lower loss.

To properly compare Red and Blue, we must thus take into account the environment, or in other words, measure how far is a policy maker from the minimum loss possible *given* the environment. This is the *Distance to Minimum Loss* (DML), defined as

$$\Delta = \mathcal{L}^0 - \mathcal{L}^{\text{opt}} \ , \tag{6}$$

and depicted in Figure 1a: the distance between the actual expected loss and the feasible minimum loss.

A sufficient statistics approach to policy evaluation

To measure the DML, one possible approach consists in specifying a structural model, fit that model to the data spanning the policy maker's term and then compute the minimum feasible loss $\mathcal{L}^{\text{opt}}$ from that model. In this example this amounts to specifying the Phillips and IS curves and estimating the associated parameters θ. A risk with this approach however is model mis-specification: if the model does not capture the full complexity of the underlying environment, the policy assessment can be compromised.

In this paper, we propose a different approach to measure Δ, an approach that requires minimal assumptions on the underlying economic model.

A class of policy rule counter-factuals To measure the minimum attainable loss $\mathcal{L}^{\text{opt}}$, we characterize the optimal reaction function ϕ^{opt} in a different way. Instead of minimizing the loss with respect to the reaction coefficients in front of endogenous variables (as is common in the literature, e.g., Galí (2015)), we propose to optimize with respect to the reaction coefficients in front of structural shocks. While this class of rule counterfactuals could seem of little direct interest, they have two important, yet overlooked, properties: (i) the effects of counterfactual reaction to structural shocks can be computed with minimal assumptions on the underlying model, depending only on estimable sufficient statistics, and (ii) the optimal reaction coefficients to structural shocks is sufficient to fully characterize the optimal policy rule, and thus to compute the minimum attainable loss.

To see that, recall that $\phi^0 = (\phi^0_\pi, \sigma^0_\epsilon)$ is the policy maker's reaction function and consider the policy rule counter-factual

$$i_t = \phi^0_\pi \pi_t + \underbrace{\sigma^0_\epsilon(\tau_\xi \xi_t + \tau_\epsilon \epsilon_t)}_{\text{Reaction adjustment}} + \sigma^0_\epsilon \epsilon_t \ , \tag{7}$$

where $\tau = (\tau_\xi, \tau_\epsilon)'$ is a vector of responses to structural shocks. Unlike the original reaction function (3), the modified reaction function (7) fixes the reaction coefficients ϕ^0 at their baseline value.

Following the same steps that led to (4), we can solve the model under that modified policy rule and express the endogenous variables as a function of exogenous shocks to get

$$Y_t = (\Gamma^0 + \mathcal{R}^0 \tau_\xi)\xi_t + (\mathcal{R}^0 + \mathcal{R}^0 \tau_\epsilon)\epsilon_t \ , \tag{8}$$

where $\Gamma^0 = \Gamma(\phi^0, \theta)$ and $\mathcal{R}^0 = \mathcal{R}(\phi^0, \theta)$.

From expression (8), we can see that $\Gamma^0 + \mathcal{R}^0 \tau_\xi$ is the impulse response to cost-push shocks *after* the reaction function adjustment τ_ξ. In other words, the adjustment τ_ξ modifies the impulse response to cost-push shocks from Γ^0 to $\Gamma^0 + \mathcal{R}^0 \tau_\xi$, which means that the "old" impulse responses Γ^0 and $\mathcal{R}^0$ are all we need to compute the effects of the policy rule counter-factual (7).

Optimal reaction adjustment From (8), we can use Γ^0 and $\mathcal{R}^0$ to search for the optimal reaction coefficient to structural shocks. To that effect, it is helpful to define an auxiliary loss function that takes τ, the vector of reaction coefficients to shocks, as its arguments while holding ϕ^0 fixed.

$$\mathsf{L}(\tau;\phi^0,\theta) \quad = \quad \mathsf{L}_\xi(\tau_\xi;\phi^0,\theta) + \mathsf{L}_\epsilon(\tau_\epsilon;\phi^0,\theta) \ . \tag{9}$$

with $\mathsf{L}_\xi(\tau_\xi;\phi^0,\theta) = \|\Gamma^0 + \mathcal{R}^0\tau_\xi\|^2$ and $\mathsf{L}_\epsilon(\tau_\epsilon;\phi^0,\theta) = \|\mathcal{R}^0 + \mathcal{R}^0\tau_\epsilon\|^2$.

By construction when $\tau = 0$ the auxiliary loss function coincides with $\mathcal{L}^0$, the baseline loss taken at the policy makers choice ϕ^0. Then, starting from that baseline $\mathcal{L}^0$ with $\tau = 0$, the auxiliary loss traces how a reaction adjustment τ affects the baseline loss, either through τ_ξ and its effect on the impulse responses to cost-push shock or through τ_ϵ and its effect on the impulse responses to policy shocks.

Overall, the auxiliary loss function is different from the original loss function $\mathcal{L}(\phi;\theta)$ (Figure 1a for an illustration), but its key property is that it has the same minimum as the original loss function $\mathcal{L}(\phi;\theta)$, i.e., the same minimum $\mathcal{L}^{\text{opt}}$. To show that, we can solve for the optimum reaction adjustment τ^* with

$$\tau^* = \arg\min_\tau \mathsf{L}(\tau;\phi^0,\theta) \ , \qquad \Rightarrow \qquad \tau^*_\xi = -(\mathcal{R}^{0\prime}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\Gamma^0 \quad \text{and} \quad \tau^*_\epsilon = -1 \ . \tag{10}$$

The statistic τ^* is the Optimal Reaction Adjustment (ORA):[5] (i) it adjusts the reaction to non-policy shocks ξ_t in order to minimize their effects, i.e., to reach Γ^{opt}; the minimal effect of cost-push shock that a policy maker can achieve given the environment θ, and (ii) it cancels monetary mistakes by setting policy shocks back to zero with $\tau^*_\epsilon = -1$.

Distance to minimum loss While the ORA itself may not be of direct interest to policy makers—the ORA is a reaction coefficient to unobserved structural shocks instead of endogenous variables—, its importance comes from its one key property: it allows to fully characterize the optimal reaction function and thereby compute the minimum loss.[6]

Indeed, we have

$$\mathsf{L}(\tau^*;\phi^0,\theta) = \mathcal{L}^{\text{opt}} \ . \tag{11}$$

[5]Note how τ^*_ξ is the coefficient of a regression of Γ^0 on $-\mathcal{R}^0$; a regression in impulse response space. Intuitively, Γ^0 (the impulse response to a cost-push shock) captures what the policy maker *did* on average to counteract cost-push shocks with his rule ϕ^0, while $\mathcal{R}^0$ (the impulse response to a monetary shock) captures what the policy maker *could have done* to counteract cost-push shocks —how reacting to ξ_t by τ could have better stabilized the effect of cost-push shocks by transforming Γ^0 into $\Gamma^0 + \tau\mathcal{R}^0$, see (8)—. A regression on $\mathcal{R}^0$ on Γ^0 precisely finds the τ that minimizes the sum-of-squares of that adjusted impulse response, i.e., that best cancels out the effects of non-policy shock. At an optimal policy rule, Γ^0 and $\mathcal{R}^0$ should be orthogonal.

[6]Note that the optimal reaction coefficients τ^* can also be used to recover ϕ^{opt} —the optimal coefficients of the instrument rule—, but this requires specifying a functional form for the policy instrument rule; an extra assumption that is not needed for computing τ^*.

This means that the auxiliary loss function $\mathsf{L}(\tau;\phi^0,\theta)$ has the same minimum as the original loss function $\mathcal{L}(\phi;\theta)$.[7]

Figure 1b traces out the auxiliary loss function (9) as a function of τ_ξ.

From those two points, we can compute the distance to minimum loss Δ based on

$$\Delta = \mathcal{L}^0 - \mathcal{L}^{\text{opt}} = \Delta_\xi + \Delta_\epsilon \ , \tag{12}$$

where

$$\Delta_\xi = \Gamma^{0\prime}\mathcal{R}^0\left(\mathcal{R}^{0\prime}\mathcal{R}^0\right)^{-1}\mathcal{R}^{0\prime}\Gamma^0 \qquad \text{and} \qquad \Delta_\epsilon = \mathcal{R}^{0\prime}\mathcal{R}^0 \ . \tag{13}$$

The expression shows that the DML can be computed from the impulse responses to policy and non-policy shocks, i.e. $\mathcal{R}^0$ and Γ^0.

Figure 1 summarizes the main idea underlying our approach. Looking at both panels, the DML can be computed either from the original loss function or from the auxiliary loss function. By going through the auxiliary loss function (i.e., by studying how the loss depends on the policy maker's systematic reaction to structural shocks), we can compute the DML with minimal assumptions on the underlying model, as the derivatives of the auxiliary loss function depend only on estimable sufficient statistics: the impulse responses $\mathcal{R}^0$ and Γ^0. Figure 1b also illustrates how the ORA and DML can be seen as two sides of the same coin —two complementary ways to evaluate a policy maker—. The ORA measures how far is a policy maker's reaction coefficient from the optimal reaction coefficient, while the DML captures the "welfare" consequences of that sub-optimal reaction coefficient.

In sum, this example illustrates how we can evaluate and compare policy makers based on their DML without specifying an explicit reaction function nor a specific structural macro model. Instead, the only requirement is to estimate two sufficient statistics: the impulse responses Γ and $\mathcal{R}$ over a policy maker's term. The next sections show that these findings continue to hold for general linear forward looking macro models.

3 Environment

We describe a general stationary macro environment for a policy maker (or institution) who faces an infinite horizon economy. To describe the economy we distinguish between two types

[7]To see this plug in τ^* into the auxiliary loss function to obtain

$$\begin{aligned} \mathsf{L}(\tau^*;\phi^0,\theta) &= \Gamma^{0\prime}(I - \mathcal{R}^0(\mathcal{R}^{0\prime}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime})\Gamma^0 \\ &= \frac{\sigma_\xi^2}{1+\kappa^2} = \mathcal{L}(\phi^{\text{opt}};\theta) \ , \end{aligned}$$

using the expressions for Γ^0 and $\mathcal{R}^0$.

of observable variables: policy instruments $p_t \in \mathbb{R}^{M_p}$ and non-policy variables $y_t \in \mathbb{R}^{M_y}$. The policy instruments are different from the other variables as they are under the direct control of the policy maker.

To describe the economy we use a sequence space representation (e.g., Auclert et al., 2021). Let $\mathbf{P} = (p_0', p_1', \ldots)'$ and $\mathbf{Y} = (y_0', y_1', \ldots)'$ denote the paths for the policy instruments and non-policy variables. Working under perfect foresight, we consider a generic model for the paths of the endogenous variables

$$\begin{array}{rcl} \mathcal{A}_{yy}\mathbf{Y} - \mathcal{A}_{yp}\mathbf{P} & = & \mathcal{B}_{y\xi}\mathbf{\Xi} \\ \mathcal{A}_{pp}\mathbf{P} - \mathcal{A}_{py}\mathbf{Y} & = & \mathcal{B}_{p\xi}\mathbf{\Xi} + \mathcal{B}_{p\epsilon}\boldsymbol{\epsilon} \end{array}, \tag{14}$$

where $\boldsymbol{\epsilon} = (\epsilon_0', \epsilon_1', \ldots)'$ and $\mathbf{\Xi} = (\xi_0', \xi_1', \cdots)'$ are sequences of policy and non-policy shocks, respectively. The first equation captures the non-policy block of the economy, while the second equation captures the policy rule.

We normalize all elements of $\mathbf{\Xi}$ and $\boldsymbol{\epsilon}$ to have mean zero and unit variance.[8] Also, we assume that they are serially and mutually uncorrelated, consistent with the common definition of structural shocks (e.g. Bernanke, 1986; Ramey, 2016).[9] The structural maps $\mathcal{A}_{..}$ and $\mathcal{B}_{..}$ are conformable and may depend on underlying structural parameters. We conveniently split them in two parts: the economic environment $\theta = \{\mathcal{A}_{yy}, \mathcal{A}_{yp}, \mathcal{B}_{y\xi}\}$ which the policy maker takes as given, and the reaction function $\phi = \{\mathcal{A}_{pp}, \mathcal{A}_{py}, \mathcal{B}_{p\xi}, \mathcal{B}_{p\epsilon}\}$, which is under the control of the policy maker and we assume that $\mathcal{B}_{p\epsilon}$ is invertible. Further, we impose that ϕ and θ are independent in the sense that $\partial\theta_i/\partial\phi_j = 0$ for all entries i, j, i.e. changing the reaction function does not directly change the coefficients θ and all effects of ϕ on $\mathbf{Y}$ go via the policy path $\mathbf{P}$.

We denote by Φ the set of all reaction functions ϕ for which the model (14) implies a unique equilibrium, that is all ϕ for which

$$\mathcal{A} = \begin{pmatrix} \mathcal{A}_{yy} & \mathcal{A}_{yp} \\ \mathcal{A}_{py} & \mathcal{A}_{pp} \end{pmatrix} \qquad \text{is invertible.}$$

Many structural models found in the literature can be written in the form of (14); prominent examples include New Keynesian models and heterogeneous agents models.

For any $\phi \in \Phi$ we can write the expected path of the non-policy variables as a linear function of the policy and non-policy shocks.

[8] The unit variance normalization is without loss of generality as the elements of $\mathcal{B}_{..}$ are unrestricted.

[9] Note that if the elements of $\mathbf{\Xi}$ or $\boldsymbol{\epsilon}$ are not serially uncorrelated it is always possible to redefine $\mathcal{B}_{y\xi}, \mathcal{B}_{p\xi}$ and $\mathcal{B}_{p\epsilon}$ such that the equation residuals —the shocks— are uncorrelated. For example if $\text{var}(\mathbf{\Xi}) = \Sigma$, then redefine $\mathcal{B}_{y\xi}\mathbf{\Xi} = \tilde{\mathcal{B}}_{y\xi}\tilde{\mathbf{\Xi}}$ with $\tilde{\mathcal{B}}_{y\xi} = \mathcal{B}_{y\xi}\Sigma^{1/2}$ and $\tilde{\mathbf{\Xi}} = \Sigma^{-1/2}\mathbf{\Xi}$ such that $\tilde{\mathbf{\Xi}}$ is serially uncorrelated. The same can be done for $\mathcal{B}_{p\xi}\mathbf{\Xi}$ or $\mathcal{B}_{p\epsilon}\boldsymbol{\epsilon}$.

Lemma 1. *Given the generic model* (14) *with* $\phi \in \Phi$*, we have*

$$\mathbf{Y} = \Gamma(\phi, \theta)\boldsymbol{\Xi} + \mathcal{R}(\phi, \theta)\boldsymbol{\epsilon} \ . \tag{15}$$

The maps $\Gamma(\phi, \theta)$ and $\mathcal{R}(\phi, \theta)$ capture the causal effects of the structural shocks $\boldsymbol{\Xi}$ and $\boldsymbol{\epsilon}$ on the non-policy variables. Explicit characterizations for $\Gamma(\phi, \theta)$ and $\mathcal{R}(\phi, \theta)$ are given in the appendix. Note the similarity between (15) and (4), as the illustrative static NK model is a special case with only contemporaneous shocks.

Lemma 1 implies that the identification of the impulse responses requires observing part of the *future* shocks in $\boldsymbol{\Xi}$ and $\boldsymbol{\epsilon}$. That is, news shocks at the different horizons are needed for identification.

Evaluation criteria

We consider a researcher who is interested in evaluating a policy maker based on her success at stabilizing some subset of the non-policy variables y_t around some desired targets y^* for some time periods $t = 0, 1, 2, \ldots$. For ease of notation we will set the targets to zero, as we can think of y_t as defined in deviation from the desired targets. In general, we will see that the target values y^* are not needed to evaluate reaction functions.

We measure performance using the loss function

$$\mathcal{L}(\phi; \theta) = \mathbb{E}\mathbf{Y}'\mathcal{W}\mathbf{Y} \ , \tag{16}$$

where $\mathcal{W}$ is a diagonal matrix, with non-negative entries, which selects and weights the specific variables and horizons that are part of the researcher's evaluation criteria. The loss (16) is the researcher's evaluation criterion for scoring policy maker performance —an input into our framework—.

The actions of the policy maker are summarized by the reaction function ϕ. We define a reaction function to be optimal if it minimizes the loss function (16). Formally, the set of optimal reaction functions is given by

$$\Phi^{\text{opt}} = \left\{ \phi : \phi \in \underset{\phi \in \Phi}{\operatorname{argmin}} \, \mathcal{L}(\phi; \theta) \quad \text{s.t} \quad (14) \right\} \ . \tag{17}$$

The definition implies that we only consider optimal reaction functions that lie in Φ; the set of reaction functions which imply a unique equilibrium.

4 Policy evaluation with sufficient statistics

In this section, we show how we can evaluate a policy maker after her term by measuring the distance between the loss under her reaction function, denoted by ϕ^0, and the loss under the optimal reaction function. To that effect, we define the *Distance to Minimum Loss* (DML) as

$$\Delta = \mathcal{L}^0 - \mathcal{L}^{\text{opt}} \ , \tag{18}$$

where $\mathcal{L}^0 = \mathcal{L}(\phi^0; \theta)$ is the loss under the actual rule ϕ^0 and $\mathcal{L}^{\text{opt}} = \mathcal{L}(\phi^{\text{opt}}; \theta)$ is the loss under an optimal rule $\phi^{\text{opt}} \in \Phi^{\text{opt}}$ as defined in (17).

4.1 Computing the distance to minimum loss

Following the same steps as the simple example of Section 2, we propose to measure the DML by considering a thought experiment where we adjust the policy maker's reaction coefficients to the structural shocks. Specifically, consider the auxiliary reaction function

$$\mathcal{A}^0_{pp}\mathbf{P} - \mathcal{A}^0_{py}\mathbf{Y} = \mathcal{B}^0_{p\xi}\boldsymbol{\Xi} + \mathcal{B}^0_{p\epsilon}\boldsymbol{\epsilon} + \mathcal{B}^0_{p\epsilon}(\mathcal{T}_\xi\boldsymbol{\Xi} + \mathcal{T}_\epsilon\boldsymbol{\epsilon}) \ , \tag{19}$$

where $\mathcal{T} = (\mathcal{T}_\xi, \mathcal{T}_\epsilon)$ adjusts the response to the structural shocks $\boldsymbol{\Xi}$ and $\boldsymbol{\epsilon}$.[10] Each element of $\mathcal{T}$ corresponds to a different rule counterfactual, in which we modify how one element of the policy path responds to one of the shocks.

The following lemma establishes how a rule adjustment $\mathcal{T}$ affects the equilibrium allocation

Lemma 2. *Consider the generic model* (14) *with* $\phi^0 \in \Phi$ *and the modified policy rule* (19)*. We have*

$$\mathbf{Y} = (\Gamma^0 + \mathcal{R}^0\mathcal{T}_\xi)\boldsymbol{\Xi} + (\mathcal{R}^0 + \mathcal{R}^0\mathcal{T}_\epsilon)\boldsymbol{\epsilon} \ , \tag{20}$$

where $\Gamma^0 \equiv \Gamma(\phi^0, \theta)$ *and* $\mathcal{R}^0 \equiv \mathcal{R}(\phi^0, \theta)$.

The reaction adjustment $\mathcal{T}$ affects the equilibrium by changing the impulse responses to non-policy shocks from Γ^0 to $\Gamma^0 + \mathcal{R}^0\mathcal{T}_\xi$ and the impulse responses to policy shock from $\mathcal{R}^0$ to $\mathcal{R}^0 + \mathcal{R}^0\mathcal{T}_\epsilon$, so that knowledge of the impulse response matrix $\mathcal{R}^0$ is sufficient to compute the policy rule counterfactuals embedded in the $\mathcal{T}$ adjustments.

[10] To help understand the elements of $\mathcal{T}$ in this sequence-space representation, imagine that there is only one policy instrument and one type of non-policy shock: an oil price shock. The upper-left element of $\mathcal{T}_\xi$ ($\mathcal{T}_{\xi,00}$) is an adjustment to the contemporaneous response of the policy instrument to a contemporaneous oil shock. The element $\mathcal{T}_{\xi,01}$ is an adjustment to the *contemporaneous* response of the policy instrument to a *news* oil shock announced today but affecting oil prices next period; the element $\mathcal{T}_{\xi,10}$ is an adjustment to the response of the policy instrument *next period* to a *contemporaneous* oil shock; and so on.

We now define the auxiliary loss function

$$\mathsf{L}(\mathcal{T};\phi^0,\theta) = \mathbb{E}\mathbf{Y}'\mathcal{W}\mathbf{Y} \qquad \text{with} \quad \mathbf{Y} = (\Gamma^0 + \mathcal{R}^0\mathcal{T}_\xi)\boldsymbol{\Xi} + (\mathcal{R}^0 + \mathcal{R}^0\mathcal{T}_\epsilon)\boldsymbol{\epsilon} \ , \tag{21}$$

which allows to trace out how changing the policy maker's reaction to any individual shock affects the loss.

The *Optimal Reaction Adjustment* (ORA) is the adjustment that minimizes the auxiliary loss function, i.e. $\mathcal{T}^* = \text{argmin}_{\mathcal{T}} \mathsf{L}(\mathcal{T};\phi^0,\theta)$, and we have

$$\mathcal{T}^* = [\mathcal{T}^*_\xi, \mathcal{T}^*_\epsilon] \qquad \text{with} \qquad \mathcal{T}^*_\xi = -(\mathcal{R}^{0'}\mathcal{W}\mathcal{R}^0)^{-1}\mathcal{R}^{0'}\mathcal{W}\Gamma^0 \quad \text{and} \quad \mathcal{T}^*_\epsilon = -\mathbf{I} \ , \tag{22}$$

where $\mathbf{I}$ is the identity map. Note that the ORA has the same geometric interpretation as discussed in the simple example, and $\mathcal{T}^*_\xi$ is equal to the (weighted) least-square regression of the selected non-policy impulse responses Γ^0 on the selected policy impulse responses $\mathcal{R}^0$. The only difference is the weighting matrix $\mathcal{W}$, which is merely a selection tool used to select the variables that comprise the researcher's evaluation criteria.

Using the ORA we can establish the following key result for the distance to minimum loss defined in (18).

Proposition 1. *Given the generic model* (14)*, with* $\phi^0 \in \Phi$*, we have that*

1. $\mathsf{L}(\mathcal{T}^*;\phi^0,\theta) = \mathcal{L}^{\text{opt}}$
2. *The DML statistic* $\Delta = \mathcal{L}^0 - \mathcal{L}^{\text{opt}} = \Delta_\xi + \Delta_\epsilon$ *where*

$$\Delta_\xi = \text{Tr}(\Gamma^{0'}\mathcal{W}\mathcal{R}^0(\mathcal{R}^{0'}\mathcal{W}\mathcal{R}^0)^{-1}\mathcal{R}^{0'}\mathcal{W}\Gamma^0) \qquad \textit{and} \qquad \Delta_\epsilon = \text{Tr}(\mathcal{R}^{0'}\mathcal{W}\mathcal{R}^0) \ .$$

The first part of the proposition states that the auxiliary loss function, when evaluated at the ORA statistic, attains the minimum loss as defined in (18). This is our identification result: knowledge of the optimal reaction to the different structural shocks is sufficient to fully characterize the optimal policy rule and thus to compute the minimum attainable loss $\mathcal{L}^{\text{opt}}$. The second part of the proposition states that the DML —the distance between $\mathcal{L}^0$ and $\mathcal{L}^{\text{opt}}$— can be computed from sufficient statistics alone:—the impulse responses $\mathcal{R}^0$ and Γ^0 to policy and non-policy shocks—.

4.2 Policy evaluation with subset shock identification

Identifying the ORA and the DML requires the identification of all the elements of $\mathcal{R}^0$ and Γ^0 which in turn requires to identify all the different types of non-policy shocks that affected the economy (including news shocks) as well as all the different policy shocks (including news shocks). In practice, this may not be possible, and a researcher may only be able to estimate a subset of all policy and non-policy shocks. Fortunately, it is possible to evaluate policy makers even with subset shock identification.

To formalize this, let $\boldsymbol{\epsilon}_a$ denote any subset of $\boldsymbol{\epsilon}$ and $\boldsymbol{\Xi}_b$ denote any subset of $\boldsymbol{\Xi}$. The corresponding sets of impulse responses are denoted by $\mathcal{R}_a$ and Γ_b. To measure the corresponding subset distance to minimum loss, we proceed similarly to Section 4.1. That is we consider the augmented policy rule

$$\mathcal{A}^0_{pp}\mathbf{P} - \mathcal{A}^0_{py}\mathbf{Y} = \mathcal{B}^0_{p\xi}\boldsymbol{\Xi} + \mathcal{B}^0_{p\epsilon}\boldsymbol{\epsilon} + \mathcal{B}^0_{p\epsilon_a}(\mathcal{T}_{\xi,ab}\boldsymbol{\Xi}_b + \mathcal{T}_{\epsilon,aa}\boldsymbol{\epsilon}_a) \ , \tag{23}$$

where now only the responses to the identifiable shocks are adjusted by $\mathcal{T}_{ab} = (\mathcal{T}_{\xi,ab}, \mathcal{T}_{\epsilon,aa})$. The auxiliary loss function $\mathsf{L}(\mathcal{T}; \phi^0, \theta)$ in (21) allows to trace out the consequences of modifying $\mathcal{T}_{ab}$. Slightly abusing notation, we define $\mathsf{L}(\mathcal{T}_{ab}; \phi^0, \theta) = \mathsf{L}(\mathcal{T}_{ab}, \mathcal{T}_{-a,-b} = 0; \phi^0, \theta)$ where the not adjusted coefficients $\mathcal{T}_{-a,-b}$ are set to zero. Using the auxiliary loss function we can compute the optimal reaction adjustment for $\mathcal{T}_{ab}$ and subsequently define the subset distance to minimum loss. The following proposition summarizes the results.

Proposition 2. *Given the generic model* (14)*, with $\phi^0 \in \Phi$, we have that*

1. $\mathcal{L}^{\text{opt}} \leq \mathsf{L}(\mathcal{T}^*_{ab}; \phi^0, \theta) \leq \mathcal{L}^0$ *for the subset ORA statistic* $\mathcal{T}^*_{ab} = \text{argmin}_{\mathcal{T}_{ab}} \mathsf{L}(\mathcal{T}_{ab}; \phi^0, \theta)$,

$$\mathcal{T}^*_{ab} = [\mathcal{T}^*_{\xi,ab}, \mathcal{T}^*_{\epsilon,aa}] \ , \qquad \mathcal{T}^*_{\xi,ab} = -(\mathcal{R}^{0\prime}_a \mathcal{W} \mathcal{R}^0_a)^{-1} \mathcal{R}^{0\prime}_a \mathcal{W} \Gamma^0_b \qquad \textit{and} \qquad \mathcal{T}^*_{\epsilon,aa} = -\mathbf{I}_a$$

2. *The subset DML statistic* $\Delta_{ab} = \mathcal{L}^0 - \mathsf{L}(\mathcal{T}^*_{ab}; \phi^0, \theta) = \Delta_{\xi,ab} + \Delta_{\epsilon,aa}$ *where*

$$\Delta_{\xi,ab} = \text{Tr}(\Gamma^{0\prime}_b \mathcal{W} \mathcal{R}^0_a (\mathcal{R}^{0\prime}_a \mathcal{W} \mathcal{R}^0_a)^{-1} \mathcal{R}^{0\prime}_a \mathcal{W} \Gamma^0_b) \qquad \textit{and} \qquad \Delta_{\epsilon,aa} = \text{Tr}(\mathcal{R}^{0\prime}_a \mathcal{W} \mathcal{R}^0_a)$$

3. *The subset DML bounds* $\Delta_{ab} \leq \Delta_a \leq \Delta_{ab} + \mathcal{E}^0_{ab}$*, where* $\Delta_a = \Delta_{\xi,a} + \Delta_{\epsilon,aa}$ *with* $\Delta_{\xi,a} = \text{Tr}(\Gamma^{0\prime} \mathcal{W} \mathcal{R}^0_a (\mathcal{R}^{0\prime}_a \mathcal{W} \mathcal{R}^0_a)^{-1} \mathcal{R}^{0\prime}_a \mathcal{W} \Gamma^0)$ *, and*

$$\mathcal{E}^0_{ab} \equiv \mathcal{L}^0 - \mathcal{L}^0_{ab} \qquad \textit{with} \qquad \mathcal{L}^0_{ab} = \text{Tr}(\Gamma^{0\prime}_b \mathcal{W} \Gamma^0_b) + \text{Tr}(\mathcal{R}^{0\prime}_a \mathcal{W} \mathcal{R}^0_a) \ . \tag{24}$$

The first part defines the *subset ORA* statistic $\mathcal{T}^*_{ab}$, where $\mathcal{T}^*_{\xi,ab}$ measures by how much to adjust the systematic reaction of the policy instruments a to the non-policy shocks Ξ_b in order to best lower the loss $\mathcal{L}^0$. The second part defines the *subset DML* statistic Δ_{ab} corresponding to $\mathcal{T}^*_{ab}$, i.e., the distance to minimum loss for a policy maker optimizing the reactions of her a policy instruments to the b non-policy shocks.

Each individual element of $\mathcal{T}^*_{ab}$ has an economic interpretation; corresponding to a specific action behind a suboptimal policy, i.e., a specific coefficient in the policy rule,[11] and the sub-distance Δ_{ab} provides a summary measure of overall performance for the subset of shocks we could identify.

The third part of the proposition puts bounds on Δ_a, the distance to minimum loss for the policy instruments captured by subset a, allowing to measure the "exhaustivity" of a subset policy evaluation.[12] It does so by exploiting the (estimable) *unexplained loss* $\mathcal{E}^0_{ab}$ —the loss that cannot be accounted by our subsets a and b of identified shocks—.[13] Intuitively, the lower bound corresponds to the case where the unexplained loss is already minimal, that is could not have been lowered with another reaction function, while the upper bound corresponds to the case where the unexplained loss could have been entirely set to zero with a different reaction function. The larger the fraction of the total loss that can be identified with the subset b, the tighter the confidence bounds, and thus the more exhaustive the overall policy evaluation: in the limit where we can identify all structural shocks, the unexplained loss is zero ($\mathcal{E}^0_{ab} = 0$), the upper and lower bounds coincide, and we have an exhaustive policy evaluation for the policy instruments captured by the subset a.

4.3 Ranking policy makers

Consider now a researcher aiming to compare the performance of different policy makers. Based on the previous sections we can evaluate policy makers in two ways: the distance to the optimal reaction adjustment (the ORA) and the distance to minimum loss (the DML): both depict the same sub-optimal policy but from a different angle. The ORA measures the sub-optimality of the reaction function —good policy/bad policy—, while the DML measures the consequence of that sub-optimal reaction on the loss function. Depending on the variance of the underlying shocks and on the structure of the economy (i.e., the shape of the loss function in Figure 1), the same ORA may imply small or large distances to minimum loss. This is the good luck/bad luck component of policy outcomes. For these reasons, we propose to compare policy makers based on both the ORA and the DML statistics.

Definition 1 (Ranking)**.** *Given two policy makers $j = A, B$ with $\phi^j \in \Phi$ and θ^j. Let τ^j_{lk} be the l, k entry of $\mathcal{T}^{j*}_{ab}$, and Δ^j_{lk} be the DML implied by τ^j_{lk}. We have*

- *A is ORA-ranked above B for the element lk if $|\tau^A_{lk}| < |\tau^B_{lk}|$.*

[11] To give a concrete example, say we identified contemporaneous shocks to the central bank's policy rate and contemporaneous shocks to oil prices. Then the corresponding ORA entry will assess how the policy maker used the contemporaneous policy rate to minimize the effects of contemporaneous oil shocks.

[12] For instance, if the set a only includes contemporaneous policy shocks, the distance Δ_a measures how well the policy maker used its contemporaneous policy instrument in response to *all* the non-policy shocks that could affect the economy.

[13] The unexplained loss $\mathcal{E}^0_{ab} = \mathcal{L}^0 - \mathcal{L}^0_{ab}$ is computable using the identified impulse responses (for $\mathcal{L}^0_{ab}$) and the realizations of the relevant macro variables over the policy makers term (for $\mathcal{L}^0$).

- *A is DML-ranked above B for the element lk if* $|\Delta^A_{lk}| < |\Delta^B_{lk}|$.

These rankings are shock-specific comparisons; they compare how well different policy makers reacted to the same type of non-policy shock. As such, they require the identification of the same policy and non-policy shocks across policy makers. This requires identifying the same type of shock (e.g., an oil shock vs a financial shock), as well as the same *dynamic* type of shock, for instance identifying the same *contemporaneous* oil shocks.[14] If it is not possible to identify the same dynamic type of shock across policy makers, a solution is to consider a higher level of time aggregation, as aggregating the paths in (14) to a lower frequency allows to mute dynamic heterogeneity across shocks. In the limit the policy problem becomes static; a situation where comparable dynamic profiles can always be guaranteed. In the web-appendix we explore this route in more details.

An alternative to shock-specific comparisons is to exploit the bounds on Δ_a provided by Proposition 2 and to rank policy makers based on the *total* distance to minimum loss for the policy instruments a. When the bounds do not overlap, this approach allows for an *overall* comparison of policy makers (i.e., taking into account all non-policy shocks), even when not all non-policy shocks can be identified.

5 Evaluating US monetary policy, 1879-2019

In this section we use our methodology to evaluate the conduct of monetary policy in the US over the 1879-2019 period. We consider four distinct periods: (i) the Gold Standard period 1879-1912 before the creation of the Federal Reserve, (ii) the early Fed years 1913-1941, (iii) the post World War II period 1954-1984 and (iv) the post-Volcker period 1990-2019.

During the Gold Standard period, there was no active monetary policy (the Federal Reserve did not exist yet), and we use this period as a benchmark to see what a fictional policy institution could have done in this period. The Gold Standard monetary regime is now generally considered a sub-optimal regime with excessive fluctuations in inflation and unemployment (e.g. Friedman and Schwartz, 1963). The early Fed period starts with the founding of the Fed in 1913 and ends with the US entering the second world war. The post-war period starts in 1951 with the Fed regaining some independence after the Treasury-Fed accord (e.g. Romer and Romer, 2004*a*).[15] The post Volcker period covers the Great Moderation period and ends right before the pandemic.

[14] This requirement is no different from numerous earlier works on time-varying impulse responses (e.g. Primiceri, 2005).

[15] We exclude the period covering World War II until the Treasury-Fed accord of 1951, as the Fed was financing the war effort and had no independence.

We evaluate the Fed as a policy institution based on the loss function

$$\mathcal{L} = \frac{1}{2}\mathbb{E}\sum_{h=0}^{H} \beta^h(\pi_{t+h}^2 + \lambda u_{t+h}^2) \ , \tag{25}$$

where π_t denotes the inflation gap, u_t the unemployment rate gap, β the discount factor and λ the preference parameter. While the targets π^* and u^* are irrelevant to rank/assess reaction functions,[16] we posit that $\pi^* = 2$ and $u^* = 5$ in order to compute realized losses in the naive approach that we describe next.

Our baseline choice for the loss function sets $\beta = \lambda = 1$, and we take $H = 30$ quarters, a horizon large enough to ensure that the impulse responses have time to mean-revert. The data are quarterly, inflation is measured as year-on-year inflation based on the output deflator from Balke and Gordon (1986), and the unemployment rate before 1948 is taken from the NBER Macrohistory database over 1929-1948 and extended back to 1876 by interpolating the annual series from Weir (1992) and Vernon (1994).

5.1 Naive approach

To provide a benchmark for our results, we first take a naive approach where we evaluate the Fed based on $\mathcal{L}^0$, which we estimate from realized outcomes for inflation and unemployment (Figure 2). Table 1 reports realized losses for inflation and unemployment ($\widehat{\mathcal{L}}_x = \sum_{j=t_s}^{t_e} x_j^2$ for $x = \pi, u$) as well as the total realized loss ($\widehat{\mathcal{L}}_\pi + \widehat{\mathcal{L}}_u$).

The Early Fed period comes out as the worse period by far, with losses almost an order of magnitude larger than in the other periods. This is driven by the Great Depression; not only the large increase in unemployment but also the large movements in inflation, from the high inflation of the early 20s to the large deflation of the early 30s. In comparison, the passive Gold Standard period appears much more successful, suffering only from high inflation volatility. In fact, losses during the Gold Standard period are of similar magnitudes to the losses realized during the Post World War II, being on a par in terms of unemployment losses. The only period with clear superior outcomes is the Post Volcker Period, also referred to as the Great Moderation, with both stable inflation and unemployment and thus low losses throughout.

As discussed earlier however, these macroeconomic outcomes cannot be interpreted as measures of performance —good/bad policy—, because they do not take into account the underlying environment of each specific period. To do so, we turn to the methodology proposed in this paper.

[16] The ORA only depends on impulse responses, which are path deviations following an innovation, and as such do not depend on the constant terms in $\mathbf{Y}$.

5.2 Policy evaluation with sufficient statistics

We will evaluate the monetary authorities based on how well they used the contemporaneous policy rate in response to five separate non-policy shocks: financial shocks, government spending shocks, energy price shocks, inflation expectation shocks and TFP shocks.

Econometric implementation We rely on a Bayesian structural vector autoregressive model (SVAR) that includes a proxy for the policy shock, the non-policy shock, the outcome variables π_t and u_t, the policy rate p_t, as well as possibly additional control variables w_t. During the 1879-1912 Gold Standard period where there is no policy institution, we take the 3-months treasury rate as the "policy rate" that a fictitious central bank could have controlled. For the 1913-1941 early Fed period, we use the fed discount rate as the policy rate. To capture the policy stance during the post WWII periods, we use the fed funds rate as the policy rate. The specific additional variables w_t and instruments z_t are discussed in detail below. The historical monetary data are taken from Balke and Gordon (1986).

The SVAR is specified for $y_t = (z_t^{\xi}, \pi_t, u_t, z_t^{\epsilon}, p_t, w_t')'$, where z_t^{ξ} is an instrument (or proxy) for the contemporaneous non-policy shock, z_t^{ϵ} is an instrument for the conventional contemporaneous monetary policy shock and w_t denotes additional control variables. We order the non-policy proxy first. As in Romer and Romer (2004*b*), we order the monetary proxy after unemployment and inflation (and before the federal funds rate), imposing the additional restriction that monetary policy does not affect inflation and unemployment within the period.

We estimate the reduced form of the SVAR model using standard Bayesian methods, which shrink the reduced form VAR coefficients using a Minnesota style prior. The prior variance hyper-parameters follow the recommendations in Canova (2007). We normalize all shocks such that they have unit variance which can be implemented in practice by computing the conventional one standard deviation impulse responses. This scaling ensures comparability of the shocks across periods.

With the draws of the parameters from the posterior density we can compute the impulse responses to a policy shock ϵ_t and the impulse responses to non-policy shock ξ_t. We will report the corresponding subset ORA $\mathcal{T}_{ab}^*$ and DML Δ_{ab}^* statistics, as well as the bounds on Δ_a based on Proposition 2. In addition, to better understand the reasons for a sub-optimal reaction function, we will report the ORA adjusted impulse responses $\Gamma^* = \Gamma^0 + \mathcal{R}^0 \mathcal{T}_{ab}^*$ for each element of the subset ab: these will capture how the economy how the policy instrument and the economy would have behaved under a more appropriate reaction function.

Shock identification

For each period, we identify a monetary policy shock and five non-policy shocks: financial shocks, government spending shocks, energy price shocks, inflation expectation shocks and TFP shocks.

Monetary policy shocks We will evaluate policy makers based on their *contemporaneous* policy response to exogenous shocks, aso that we need to identify contemporaneous shocks to the policy rate.

For the Post Volcker period we use the high-frequency identification (HFI) approach, pioneered by Kuttner (2001) and Gürkaynak, Sack and Swanson (2005), and we use surprises in fed funds futures prices around FOMC announcement as proxies for monetary shocks. To isolate innovations to the contemporaneous policy rate, we use surprises to fed funds futures at a short horizon, here 3-months ahead fed funds futures (FF4), which (with quarterly data) ensures that the identified shock does not include news shocks to the future path of policy.For the Post World War II period we use the Romer and Romer (2004*b*) identified monetary policy shocks as instruments. For the Early Fed period we use the Friedman and Schwartz (1963) dates extended by Romer and Romer (1989) as instruments to identify monetary policy shocks. We include five episodes —1920Q1, 1931Q3, 1933Q1, 1937Q1 and 1941Q3— where movements in money were "unusual given economic developments" (Romer and Romer, 1989). In the words of Romer and Romer (1989), these "unusual movements arose, in Friedman and Schwartz's view, from a conjunction of economic events, monetary institutions and the doctrines and beliefs of the time and of particular individuals determining policy".For the Pre Fed Gold Standard period, there is no clear baseline identification approach to identify monetary shocks, and we propose a new approach that exploits a unique feature of the Gold Standard. 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. As such, we use unanticipated large gold mine discoveries (discoveries that led to gold rushes) as an instrument for movements in the monetary base. To the extent that the timing of the discovery is unrelated to the state of the business cycle, gold mine discovery will be a valid instrument. Mirroring Gold discovery, we will also use peak mine extraction —the moment when one of these large mines reached peak production—. The supplementary material provides more discussion.

One limitation of using the "state of the art" identification scheme in each period is that we rely on a different methodology to identify the monetary shock over each period. Since each methodology has different strengths and weaknesses.[17] As robustness, we use an

[17]For instance, exogeneity and relevance may differ across instrumental variables, see e.g., Barnichon and

identification of monetary shock that is consistent across regimes, which will ensure that the monetary shocks are identified in the exact same way across regimes. Specifically, we use sign restrictions, another popular method to identify monetary shocks (e.g., Uhlig, 2005). This approach has the benefit that the same identification scheme can be implemented over the entire sampling period. With the VAR including inflation, unemployment, the policy rate and the growth rate of the monetary base, we impose the following sign restrictions: a positive monetary shock raises the short-term rate in impact, lowers money growth on impact, and lowers inflation and raises unemployment after a year. Other than that, the responses are unconstrained.

Non-policy shocks As financial shocks we use narratively identified bank panics. Each included panic was triggered by either a run on a particular trust fund or by foreign developments. The dates for the banking panics are taken from Reinhart and Rogoff (2009) and Romer and Romer (2017). To capture the severity of the bank run, each non-zero entry is rescaled by the change in the BAA-AAA spread at the time of the run, similar to the rescaling of Bernanke et al. (1997) and Romer and Romer (2017).[18] For government spending shocks we use the news shocks to defense spending as constructed in Ramey and Zubairy (2018). To identify productivity shocks we use the identification scheme of Gali (1999) and Barnichon (2010): we estimate bi-variate VARs with log output per hour and unemployment over each policy regime, and we impose long-run identifying restrictions, specifically that only productivity shocks can have permanent effects on productivity. The quarterly time series for output per hour is taken from Petrosky-Nadeau and Zhang (2021) and starts in 1890. To identify energy shocks, we extend the approach of Hamilton (1996) and Hamilton (2003) by identifying energy shocks as instances when energy price rises above its 3-year maximum or falls below its 3-year minimum. Since coal was the primary US energy source until World War II and oil only became the pre-dominant energy source after World War II, we measure energy price prices from the wholesale price index for fuel and lighting, available over 1890-2019. As measure of inflation expectations, we rely on the Livingston survey that has been continuously run over 1946-2019,[19] and includes a question about 8-months ahead inflation expectations. Prior to World War II, there are no systematic inflation expectation survey, so we instead rely on Cecchetti (1992)'s measure of 6-months ahead inflation

Mesters (2020) for a comparison of Romer and Romer (2004*b*) and Gürkaynak, Sack and Swanson (2005) proxies.

[18]Using bank runs as 0-1 dummies does not change conclusions drastically though it makes the estimates a bit less precise. Since the time series for AAA yields only start in 1919, we backcasted AAA yields before 1919 with yields on 10-year maturity government bonds from the Macro History database (Jordà et al., 2019).

[19]The Livingston survey is conducted with a pool of professional forecasters from non-financial businesses, investment banking firms, commercial banks, academic institutions, government, and insurance companies, see Leduc, Sill and Stark (2007).

expectations for the Early Fed period.[20] To identify innovations to inflation expectations, we proceed similarly to Leduc, Sill and Stark (2007) and project inflation expectations on a set of controls that include past values of inflation expectation, inflation, unemployment, lags of the 3-month and 10-year treasury rates. In addition, we also project on current and past values of the other identified non-policy shocks: financial, government spending, energy price and TFP. The idea of this exercise is to capture movements in inflation expectations that cannot be explained by the other shocks, i.e., that go above and beyond the typical effect of the non-policy shocks on inflation expectations.

5.3 Results

Before presenting our estimates for the ORA and DML statistics over the different periods, Figure 3 presents a decomposition of $\mathcal{L}^0$ based on (24). The decomposition conveys how much of the actual loss $\mathcal{L}^0$ can be explained by our identified non-policy shocks (the term $\mathcal{L}^0_{ab}$) and how much remains "unexplained" (the term $\mathcal{E}^0_{ab}$). Recall that the larger the "explained" part, the more exhaustive the policy evaluation will be, see Proposition 2.

We find that (i) our five non-policy shocks and one monetary shock explain about 60 percent of our estimate for $\mathcal{L}^0$. The period with the lowest share is the Pre-Fed period with about 40 percent and the highest share is the Early Fed with about 70 percent. Overall, these are large shares, providing reassurance that our overall policy assessment will be based on the most important disturbances that affected the economy over each period. In terms of shock composition, the main contributors in each period lines up well with common wisdom: The Early Fed is characterized by large contributions of financial shocks, monetary shocks and inflation expectation shocks (consistent with e.g., Romer, 1992). The Post WWII period is characterized by large contributions of energy and inflation expectation shocks (e.g., Blinder, 2022). The Post Volcker period is characterized by a very small loss overall (the Great Moderation).

Panel (i) of Table 2 reports our estimated subset DMLs for our five different shocks over four periods. Each subset DML captures how much loss could have been avoided with a better reaction to one of the shocks. The rightmost column reports our estimated bounds for the total DML, and that column can be seen as our overall policy evaluation for each period. It reports bounds on the total loss that could have been avoided with a better reaction function, see Proposition 2.

To appreciate the contribution of policy to these losses, Panel (ii) of Table 2 reports the

[20]Cecchetti (1992)'s measure of inflation expectations relies on Mishkin (1981)'s insight that the ex-ante real interest rate can be recovered from a projection of the ex-post real interest rate on the time t information set. The difference between the ex-ante and ex-post real interest rate provides a measure of inflation expectations.

ORA statistics computed over the four periods for our five non-policy shocks. Recall that the ORA is an adjustment to the coefficient $\mathcal{B}_{p\xi}$ in the policy rule,[21] so that a negative ORA indicates that the policy rate was set too high after a specific type of shock, either because the policy rate was increased too much or because it did not lowered enough.[22]

Our main results are summarized in the next four paragraphs. In the supplementary material, we show robustness to (a) our identification of monetary shocks, and (b) alternative periods. Overall, our results are consistent with our baseline estimates discussed below, with ORAs and DMLs of similar magnitudes and levels of statistical significance.

Result #1: Improved policy in the Post Volcker period Overall, we estimate strong improvements in the conduct of monetary policy, but *only* in the last 30 years, i.e., roughly after Volcker's dis-inflation program.

Consider first our DML bounds (Table 2, Panel (i), right column), which capture how much of the total loss could have been avoided with a more appropriate use of the contemporaneous policy rate. We can see that the Early Fed stands out with a much larger distance to minimum loss than in any other period: the DML range is comfortably outside all our other estimated ranges for the other periods. A mirror image of that Early Fed is the Post Volcker period with much superior performances: the DML range is much smaller than at any other time and lies outside all other estimated ranges. Interestingly, the Post WWII period and Pre Fed periods are relatively similar in terms of overall performance with similar ranges Δ.

To control for the size of the shocks as well as the underlying economic structure, i..e, to isolate the contribution of policy to these losses, we can turn to the ORAs over each period (Table 2, Panel (ii)). For the first 100 years of our study, we find *no* material improvement in the reaction function, with similar deviations from optimality over the first three periods. Comparing the rows of Table 2-Panel (ii) for the three periods before Volcker, we can see ORAs of similar magnitudes with the average absolute ORA hovering around 0.6 for 100 years.

It is only in the last 30 years that we can detect improvements in the reaction function. In the post Volcker period, the ORAs are substantially smaller (and non-significant) than in the other periods, with an average absolute ORA of 0.2.[23] In fact, the Post Volcker

[21]For instance, an ORA of 0.5 means that in response to a 1 standard deviation non-policy shock, the reaction coefficient should have been 0.5 point larger.

[22]Comparing the subset ORAs across periods requires identifying the same type of non-policy shock across periods. To assess robustness of our results to dynamic shock heterogeneity across periods, the supplementary material reports the ORA statistics estimated for a higher level of time aggregation, with impulse responses averaged over 3-year windows. The results are very similar to our baseline results in Table 2, indicating that dynamic shock heterogeneity appears to be a minor concern for our Fed comparison across periods.

[23]Importantly, the non-significance of the Post Volcker ORAs is *not* due to imprecisely estimated impulse responses. As we show in the Appendix, the Post Volcker impulse responses are estimated with reasonable

ORA statistics are smaller across *all* non-policy shocks, meaning that policy performance improves in all dimensions, from the responses to supply-type shocks like energy price shocks and TFP shocks to the responses to demand-type shocks like government spending shocks and financial shocks. That said, the consequences of these sub-optimal reaction functions are very different across periods.

In terms of policy shocks however, i.e., deviations from a stable reaction function, the conduct of policy did improve substantially before Volcker. While the early Fed stands out with a large DML Δ_ϵ and the Fed being directly responsible for large disturbances affecting the economy, the post World War II sees a much smaller Δ_ϵ. In other words, even though the reaction function is not substantially superior in the post WWII period, erratic behavior in the conduct of policy was much improved after WWII, in contrast to the stop-and-go policies of the 30s or the over-reaction of the early 20s (e.g., Friedman and Schwartz, 1963; Romer, 1992).

Result #2: Responding to financial shocks We will now focus in more details on the reaction to financial shocks, contrasting the Post Volcker Fed with the Early Fed of the 1920s-1930s. In a 2002 speech in honor of Milton Friedman 90th birthday, (then) Fed governor Bernanke famously said: "Regarding the Great Depression. You're right, we did it. We're very sorry. But thanks to you, we won't do it again." (Bernanke, 2002). In an irony of history, the speech was made a full five years before the 2007-2008 financial crisis; a crisis that saw an unprecedented Fed response (see e.g., Bernanke, 2013) *with* Bernanke as Fed chairman.

Our results confirm Bernanke's quote, both his historical claim as well as his prophecy: the "poor" reaction function of the early Fed led to massive welfare losses, while the "good" reaction function of the Post Volcker Fed ensured little welfare losses coming from a sub-optimal reaction function.

To see this, we can first contrast the financial ORAs —the ORAs for financial shocks— estimated for the Early Fed period and for the Post Volcker period. With $\tau^* = -1.2$ (statistically significant), the Fed reaction to banking panics was too tight —a result echoing previous findings in the literature (e.g., Friedman and Schwartz, 1963; Hamilton, 1987)—. In contrast, the estimated ORA for the post Volcker Fed is four times smaller with $\tau^* = -0.3$ and not statistically significant, indicating that the post Volcker Fed period reacted much more appropriately and pointing to large improvements in the Fed's reaction to financial shocks.[24] As a result, while the 2007-2008 financial disruptions were substantial, the corre-

precisions and the point estimates are sensible. The ORAs are small, *because* the impulse responses to non-policy shocks are (almost) orthogonal to the impulse responses to policy shocks.

[24]That said, a point estimate at -0.3 indicates that the Fed should have lowered the fed funds rate more in response to financial shocks (according to the posterior mean). This could indicate that the presence of

sponding estimated DML over the post-Volcker period is tiny (0.1); two orders magnitude smaller than the DML for financial shocks for the Early Fed (27.7).

To better appreciate this reaction function improvement, Figures 4 and 5 display the impulse responses underlying the financial ORAs estimated for 1913-1941 and 1990-2019. The top rows show the impulse responses of inflation, unemployment and the interest rate to a monetary policy shock, while the bottom rows show the responses of the same variables to a financial shock.[25]

For the Early Fed period, notice how the Fed *raised* the discount rate in response to financial shocks. Combined with the decline in inflation caused by the financial shock, this means that the real policy rate increased substantially and monetary policy was contractionary, confirming earlier work on the monetary factors behind the Great Depression (e.g., Friedman and Schwartz, 1963; Hamilton, 1987). The ORA corrects this sub-optimal reaction function and turns the table on monetary policy by running an expansionary policy. To see that, Figure 4 (dashed green line) reports the ORA adjusted impulse responses. The ORA leads to a major adjustment to the policy path —the policy rate now goes down substantially on impact—, and the paths of inflation and unemployment are consequently much more stable. In contrast, for the Post Volcker period (Figure 5) the policy rate goes down following a financial shock (black line, lower-right panel), and the ORA only slightly adjusts the response of the policy rate (green line), leading to modest adjustments to the responses of inflation and unemployment.

Result #3: The Great Inflation US monetary policy during the 1970s has generally been considered poor (e.g., Romer and Romer, 2004*a*), in particular not responding more than one-to-one with changes in inflation (Clarida, Galí and Gertler, 2000) and violating the so-called Taylor principle. However, beyond that Taylor principle, it has been difficult to quantify how "poor" monetary policy had been.

Overall, we find that the Fed's reaction function during the 60s-70s is on a par with the reaction function of the early Fed, with ORAs of similar magnitudes, though the nature and the sizes of the underlying shocks is different. Post World War II, the Fed reaction was too weak following all the different supply-type shocks that we identified: energy price shocks, TFP shocks as well as inflation expectation shocks. In fact, the reaction to inflation expectation shocks over the 60s-70s displays the largest deviation from optimality over the entire 150 year of monetary history with $\tau^* = 1.2$, even slightly larger (in absolute value)

the zero lower bound may have limited somewhat the Fed's ability to best react to the 2007-2008 financial crisis.

[25] For both periods, a higher policy rate raises unemployment and lowers inflation, while a financial shock lowers inflation and raises unemployment. That said, the inflation response is more muted in the post-Volcker period, consistent with the anchoring of inflation expectations post Volcker or more generally with different economies across historical periods.

than the Fed's poor reaction to bank runs during the Great Depression. The consequences of these sub-optimal reactions were much smaller however, with DMLs an order of magnitude smaller for the Post WWII period than for the Early Fed period.[26]

To illustrate these sub-optimal reaction functions, Figure 6 plots the impulse responses underlying the ORAs for inflation expectation shocks. In response to an inflation expectation shock, inflation rises progressively, but the policy rate does not respond, leading to negative real interest rates and further increasing inflation. The (large) ORA adjustment restores the Taylor principle: after the ORA, the policy rate rises strongly following an inflation expectation shock (lower-right panel, Figure 6) and stems the rise in inflation (at the cost of higher unemployment).

Result #4: The early Fed vs the passive Gold Standard In contrast to the suggestive evidence of the naive approach (Table 1), the passive Gold Standard is *not* markedly superior to the early Fed. In other words, the founding of the Fed did not deteriorate performance relative to the passive monetary regime of the Gold Standard. Instead, the reaction functions were just as "bad" before and after the founding of the Fed, though the consequences (in terms of loss) were much larger for the Early Fed period.

Comparing the ORA before and after the founding of the Fed (Table 2-Panel (ii)), we observe similar deviations from optimality. During the passive Gold Standard, monetary policy is (unsurprisingly) too passive in the face of adverse shocks: be it bank runs or military buildups.[27] Comparing ORAs across two the periods, we can see that (i) the excessive passivity simply continued after the founding of the Fed —the ORAs are similar across the two periods—, and (ii) the excessive passivity of the early Fed is not limited to financial distress, and it also extends to other shocks, here government spending shocks.[28]

6 Conclusion

In this paper, we proposed to evaluate makers based on their *distance to minimum loss* (DML): the distance to the minimum attainable loss given the economic environment. We showed that this approach can be implemented with minimal assumptions on the underlying structural economic model, because the DML can be computed from two sets of sufficient

[26]There are two possible reasons why a given ORA translates into larger losses and hence into a larger DML: (i) the magnitudes of the shocks themselves were larger in the Early Fed period, and/or (ii) the Early Fed economy was less resilient in the face of adverse disturbances than the post WWII economy.

[27]To give a few noteworthy "misses" of the passive Gold Standard, the ORAs call for lower interest rates (about 3/4 ppt) in the aftermaths of the 1893 and 1907 bank runs, as well as higher interest rates in response to higher military spending following the war against Spain in 1898, and the navy build-up of 1902-1904.

[28]In particular, we find that the Fed's delayed reaction to the large increase in military spending in 1917 is responsible for some of the inflation outburst of 1919-1920 (see also Romer, 1992).

statistics: (i) the impulse responses of the policy objectives to non-policy shocks, and (ii) the same impulse responses to policy shocks.

We evaluate US monetary policy over the past 150 years, where we find no material improvement in the reaction function over the first 100 years, but large and uniform improvements in the last 30 years. A better understanding of the functioning of the economy (Friedman and Schwartz, 1963), better and more timely data (Romer, 1986; Orphanides, 2001), better forecasting (Dominguez, Fair and Shapiro, 1988) and better causal inference methods (Romer and Romer, 1989) could all be part of the improvements in policy over the last 30 years. Parsing out these different reasons is an important question for future research.

Going forward, our proposed methodology could be applied to many other important evaluation questions; in the context of monetary policy (e.g., comparing central banks such as the Fed vs the ECB during the Great Recession), in the context of fiscal policy (e.g., comparing the performance of US presidents, health policy (e.g., comparing governments' policy responses to COVID), or climate change mitigation policy. We leave these questions for future research.

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Appendix : Details and Proofs

Proof of Lemma 1. Define

$$\mathcal{A} = \begin{bmatrix} \mathcal{A}_{yy} & \mathcal{A}_{yp} \\ \mathcal{A}_{py} & \mathcal{A}_{pp} \end{bmatrix} \ , \ \mathcal{B}_\xi = \begin{bmatrix} \mathcal{B}_{y\xi} \\ \mathcal{B}_{p\xi} \end{bmatrix} \ , \ \mathbf{J} = \begin{bmatrix} \mathbf{0} \\ \mathcal{B}_{p\epsilon} \end{bmatrix} \text{ and } \mathbf{Z} = \begin{bmatrix} \mathbf{Y} \\ \mathbf{P} \end{bmatrix} \ . \tag{26}$$

The model (14) is equivalent to

$$\mathcal{A}\mathbf{Z} = \mathcal{B}_\xi \boldsymbol{\Xi} + \mathbf{J}\boldsymbol{\epsilon} \ .$$

For any $\phi \in \Phi$ we have that there exists unique equilibrium representation. This implies that $\mathcal{A}$ is invertible and we obtain

$$\mathbf{Z} = \underbrace{\mathcal{A}^{-1}\mathcal{B}_\xi}_{=\mathcal{D}_1} \boldsymbol{\Xi} + \underbrace{\mathcal{A}^{-1}\mathbf{J}}_{=\mathcal{D}_2} \boldsymbol{\epsilon} \ .$$

The block structure of $\mathcal{D}_1$ and $\mathcal{D}_2$ is given by

$$\mathcal{D}_1 = \begin{bmatrix} \Gamma(\phi,\theta) \\ \Gamma_p(\phi,\theta) \end{bmatrix} \quad \text{and} \quad \mathcal{D}_2 = \begin{bmatrix} \mathcal{R}(\phi,\theta) \\ \mathcal{R}_p(\phi,\theta) \end{bmatrix} \ ,$$

where the maps $\Gamma(\phi,\theta)$ and $\mathcal{R}(\phi,\theta)$ appear in the first position as they capture the effects of the shocks on $\mathbf{Y}$. The other maps capture the effects of the shocks on $\mathbf{P}$. Explicit expression can be obtained by by noting that $\mathcal{A}$ being invertible implies that $\mathcal{A}_{pp}$ and $\mathcal{A}_{yy} - \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{A}_{py}$ are invertible as $\mathcal{A}_{yy}$ is generally not invertible. We have

$$\Gamma(\phi,\theta) = \mathcal{D}(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi}) \qquad \text{and} \qquad \mathcal{R}(\phi,\theta) = \mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\epsilon} \ , \tag{27}$$

with $\mathcal{D} = (\mathcal{A}_{yy} - \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{A}_{yp})^{-1}$. □

Proof of Lemma 2. Given some $\phi \in \Phi$ we can follow the same steps as the proof of Lemma 1 but using an augmented policy rule

$$\mathcal{A}_{pp}\mathbf{P} - \mathcal{A}_{py}\mathbf{Y} = (\mathcal{B}_{p\xi} + \mathcal{B}_{p\epsilon}\mathcal{T}_\xi)\boldsymbol{\Xi} + (\mathcal{B}_{p\epsilon} + \mathcal{B}_{p\epsilon}\mathcal{T}_\epsilon)\boldsymbol{\epsilon} \ ,$$

and we obtain the equilibrium representation

$$\mathbf{Y} = (\Gamma(\phi,\theta) + \mathcal{R}(\phi,\theta)\mathcal{T})\boldsymbol{\Xi} + (\mathcal{R}(\phi,\theta) + \mathcal{R}(\phi,\theta)\mathcal{T}_\epsilon)\boldsymbol{\epsilon} \ , \tag{28}$$

where

$$\Gamma(\phi,\theta) = \mathcal{D}(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi}) \qquad \text{and} \qquad \mathcal{R}(\phi,\theta) = \mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\epsilon} \ ,$$

with $\mathcal{D} = (\mathcal{A}_{yy} - \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{A}_{yp})^{-1}$. We obtain Lemma 2 for $\phi = \phi_0$. $\square$

Proof of Proposition 1. Part 1 requires showing $\mathcal{L}^{\text{opt}} = \mathsf{L}(\mathcal{T}^*; \phi^0, \theta)$. To do so we proceed mechanically and show $\{\min_\phi \mathcal{L} \text{ s.t. } (14)\} = \{\min_\mathcal{T} \mathsf{L}(\mathcal{T}; \phi^0, \theta) \text{ s.t. } (14) \text{ with } \mathcal{A}_{pp} = \mathcal{A}_{pp}^0,\ \mathcal{A}_{py} = \mathcal{A}_{py}^0, \mathcal{B}_{p\xi} = \mathcal{B}_{p\xi}^0,\ \mathcal{B}_{p\epsilon} = \mathcal{B}_{p\epsilon}^0\}$. Note that $\mathbf{Y}$ can be written as $\mathbf{Y} = (\mathcal{D}\mathcal{B}_{y\xi} + \mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})\boldsymbol{\Xi} + \mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\epsilon}\boldsymbol{\epsilon}$ Using that the entries of $\boldsymbol{\Xi}$ and $\boldsymbol{\epsilon}$ have mean zero, unit variance and are uncorrelated we have that

$$
\begin{aligned}
\mathcal{L} =& \mathbb{E}(\mathbf{Y}'\mathcal{W}\mathbf{Y}) \\
=& \text{Tr}((\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})'\mathcal{D}'\mathcal{W}\mathcal{D}(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})) \\
&+ \text{Tr}((\mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\epsilon})'\mathcal{W}\mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\epsilon}) \ .
\end{aligned}
$$

Regardless of the values of $\{\mathcal{A}_{pp}, \mathcal{A}_{py}, \mathcal{B}_{p\xi}\}$ the optimal solution for $\mathcal{B}_{p\epsilon}$ satisfies $\mathcal{B}_{p\epsilon}^{\text{opt}} = \mathbf{0}$. After setting $\mathcal{B}_{p\epsilon} = \mathcal{B}_{p\epsilon}^{\text{opt}}$ the derivative maps of $\mathcal{L}$ with respect to $\{\mathcal{A}_{pp}, \mathcal{A}_{py}, \mathcal{B}_{p\xi}\}$ are given by

$$
\begin{aligned}
\mathcal{A}_{pp}^{-1'}\mathcal{A}_{yp}'\mathcal{D}'\mathcal{W}\mathcal{D}(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})\mathcal{B}_{p\xi}'\mathcal{A}_{pp}^{-1'} + \\
\mathcal{A}_{pp}^{-1'}\mathcal{A}_{yp}'\mathcal{D}'\mathcal{W}\mathcal{D}(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})'\mathcal{D}'\mathcal{A}_{py}'\mathcal{A}_{pp}^{-1'} &= \mathbf{0} \\
\mathcal{A}_{pp}^{-1'}\mathcal{A}_{yp}'\mathcal{D}'\mathcal{W}\mathcal{D}(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi})'\mathcal{D}' &= \mathbf{0} \\
\mathcal{A}_{pp}^{-1'}\mathcal{A}_{yp}'\mathcal{D}'\mathcal{W}\mathcal{D}(\mathcal{B}_{y\xi} + \mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi}) &= \mathbf{0}
\end{aligned}
$$

The last equation gives the derivative map with respect to $\mathcal{B}_{p\xi}$. Solving this expression for $\mathcal{B}_{p\xi}$ yields

$$
\mathcal{B}_{p\xi}^{\text{opt}} = -[\mathcal{A}_{pp}^{-1'}\mathcal{A}_{yp}'\mathcal{D}'\mathcal{W}\mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}]^{-1}\mathcal{A}_{pp}^{-1'}\mathcal{A}_{yp}'\mathcal{D}'\mathcal{W}\mathcal{D}\mathcal{B}_{y\xi} \ .
$$

Further, it is easy to see that if the last equation holds then the first two equations also hold. This holds regardless of $\mathcal{A}_{pp}$ and $\mathcal{A}_{py}$ as long as the invertibility conditions above are satisfied. It remains to show that $\mathcal{B}_{p\xi}^{\text{opt}} = \mathcal{B}_{p\xi}^0 + \mathcal{B}_{p\epsilon}^0\mathcal{T}_\xi^*$ and $\mathcal{B}_{p\epsilon}^{\text{opt}} = \mathcal{B}_{p\epsilon}^0 + \mathcal{B}_{p\epsilon}^0\mathcal{T}_\epsilon^*$. The latter is straightforward as $\mathcal{T}_\epsilon^* = -\mathbf{I}$. For the former we have

$$
\begin{aligned}
&\mathcal{B}_{p\xi}^0 + \mathcal{B}_{p\epsilon}^0\mathcal{T}_\xi^* \\
&= \mathcal{B}_{p\xi}^0 - \mathcal{B}_{p\epsilon}^0(\mathcal{R}^{0'}\mathcal{W}\mathcal{R}^0)^{-1}\mathcal{R}^{0'}\mathcal{W}\Gamma^0 \\
&= \mathcal{B}_{p\xi}^0 - \mathcal{B}_{p\epsilon}^0((\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1}\mathcal{B}_{p\epsilon}^0)'\mathcal{W}\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1}\mathcal{B}_{p\epsilon}^0)^{-1}(\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1}\mathcal{B}_{p\epsilon}^0)'\mathcal{W}\Gamma^0 \\
&= \mathcal{B}_{p\xi}^0 - ((\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})^{-1}(\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\Gamma^0 \\
&= \mathcal{B}_{p\xi}^0 - ((\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})^{-1}(\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\mathcal{D}\mathcal{B}_{y\xi} \\
&+ ((\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})^{-1}(\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\mathcal{D}\mathcal{A}_{yp}\mathcal{A}_{pp}^{-1}\mathcal{B}_{p\xi} \\
&= -((\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})^{-1}(\mathcal{D}^0\mathcal{A}_{yp}^0(\mathcal{A}_{pp}^0)^{-1})'\mathcal{W}\mathcal{D}\mathcal{B}_{y\xi} = \mathcal{B}_{p\xi}^{\text{opt}} \ ,
\end{aligned}
$$

where the third equality uses that $\mathcal{B}^0_{p\epsilon}$ is invertible.

Part 2 uses the optimal characterization from part 1. We have

$$\begin{aligned}\Delta &= \mathcal{L}^0 - \mathcal{L}^{\text{opt}}\\ &= \text{Tr}(\Gamma^{0\prime}\mathcal{W}\Gamma^0) + \text{Tr}(\mathcal{R}^{0\prime}\mathcal{W}\mathcal{R}^0) - \text{Tr}((\Gamma^0 + \mathcal{R}^0\mathcal{T}^*_\xi)'\mathcal{W}(\Gamma^0 + \mathcal{R}^0\mathcal{T}^*_\xi))\\ &= \text{Tr}(\Gamma^{0\prime}\mathcal{W}\mathcal{R}^0(\mathcal{R}^{0\prime}\mathcal{W}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\mathcal{W}\Gamma^0) + \text{Tr}(\mathcal{R}^{0\prime}\mathcal{W}\mathcal{R}^0)\end{aligned}$$

which completes the proof. □

Proof of Proposition 2. For part 1 we note that

$$\begin{aligned}\mathcal{L}^{\text{opt}} &= \mathsf{L}(\mathcal{T}^*;\phi^0,\theta) = \underset{\mathcal{T}}{\text{argmin}}\,\mathsf{L}(\mathcal{T};\phi^0,\theta)\\ &\leq \underset{\mathcal{T}_{ab}}{\text{argmin}}\,\mathsf{L}(\mathcal{T}_{ab},\mathcal{T}_{-a,-b}=0;\phi^0,\theta) = \mathsf{L}(\mathcal{T}^*_{ab};\phi^0,\theta)\\ &\leq \mathsf{L}(\mathcal{T}_{ab}=0,\mathcal{T}_{-a,-b}=0;\phi^0,\theta) = \mathcal{L}^0\ .\end{aligned}$$

The explicit expressions for $\mathcal{T}^*_{ab}$ are found by solving the linear quadratic problem

$$\min_{\mathcal{T}_{ab}} \mathbb{E}(\mathbf{Y}'\mathcal{W}\mathbf{Y}) \quad \text{s.t.} \quad \mathbf{Y} = (\Gamma_b + \mathcal{R}_a\mathcal{T}_{\xi,ab})\mathbf{\Xi}_b + (\mathcal{R}_a + \mathcal{R}_a\mathcal{T}_{\epsilon,aa})\boldsymbol{\epsilon}_a + \Gamma_{-b}\mathbf{\Xi}_{-b} + \mathcal{R}_{-a}\boldsymbol{\epsilon}_{-a}\ ,$$

which is the equivalent of Lemma 2 when only adjusting $\mathcal{T}_{ab}$. For part 2, we use that $\mathcal{L}^0 = \text{Tr}(\Gamma^{0\prime}\mathcal{W}\Gamma^0) + \text{Tr}(\mathcal{R}^{0\prime}\mathcal{W}\mathcal{R}^0)$ and

$$\begin{aligned}\mathsf{L}(\mathcal{T}^*_{ab};\phi^0,\theta) =&\text{Tr}((\Gamma^0_b + \mathcal{R}^0_a\mathcal{T}^*_{\xi,ab})'\mathcal{W}(\Gamma^0_b + \mathcal{R}^0_a\mathcal{T}^*_{\xi,ab}))\\ &+ \text{Tr}((\mathcal{R}^0_a + \mathcal{R}^0_a\mathcal{T}^*_{\epsilon,aa})'\mathcal{W}(\mathcal{R}^0_a + \mathcal{R}^0_a\mathcal{T}^*_{\epsilon,aa}))\\ &+ \text{Tr}(\Gamma^{0\prime}_{-b}\mathcal{W}\Gamma^0_{-b}) + \text{Tr}(\mathcal{R}^{0\prime}_{-a}\mathcal{W}\mathcal{R}^0_{-a})\end{aligned}$$

Subtracting $\Delta_{ab} = \mathcal{L}^0 - \mathsf{L}(\mathcal{T}^*_{ab};\phi^0,\theta)$ gives $\Delta_{ab} = \Delta_{\xi,ab} + \Delta_{\epsilon,aa}$ with

$$\begin{aligned}\Delta_{\xi,ab} &= \text{Tr}(\Gamma^{0\prime}_b\mathcal{W}\Gamma^0_b) - \text{Tr}((\Gamma^0_b + \mathcal{R}^0_a\mathcal{T}^*_{\xi,ab})'\mathcal{W}(\Gamma^0_b + \mathcal{R}^0_a\mathcal{T}^*_{\xi,ab}))\\ &= \text{Tr}(\Gamma^{0\prime}_b\mathcal{W}\mathcal{R}^0_a(\mathcal{R}^{0\prime}_a\mathcal{W}\mathcal{R}^0_a)^{-1}\mathcal{R}^{0\prime}_a\mathcal{W}\Gamma^0_b)\end{aligned}$$

and $\Delta_{\epsilon,aa} = \text{Tr}(\mathcal{R}^{0\prime}_a\mathcal{W}\mathcal{R}^0_a)$. For part 3 we need to show that $\Delta_{ab} \leq \Delta_a \leq \Delta_{ab} + \mathcal{E}^0_{ab}$, where $\Delta_{ab} = \mathcal{L}^0 - \mathsf{L}(\mathcal{T}^*_{ab};\phi^0,\theta)$, $\Delta_a = \mathcal{L}^0 - \mathsf{L}(\mathcal{T}^*_a;\phi^0,\theta)$ and $\mathcal{E}^0_{ab} = \mathcal{L}^0 - \text{Tr}(\Gamma^{0\prime}_b\mathcal{W}\Gamma^0_b) - \text{Tr}(\mathcal{R}^{0\prime}_a\mathcal{W}\mathcal{R}^0_a)$. For the lower bound we note that $\Delta_{ab} \leq \Delta$ is implied by $\mathsf{L}(\mathcal{T}^*_{ab};\phi^0,\theta) = \mathsf{L}(\mathcal{T}^*_{ab},\mathcal{T}_{-a,-b} = 0;\phi^0,\theta) \geq \mathsf{L}(\mathcal{T}^*_a;\phi^0,\theta)$. For the upper bound $\Delta_a \leq \Delta_{ab} + \mathcal{E}^0_{ab}$

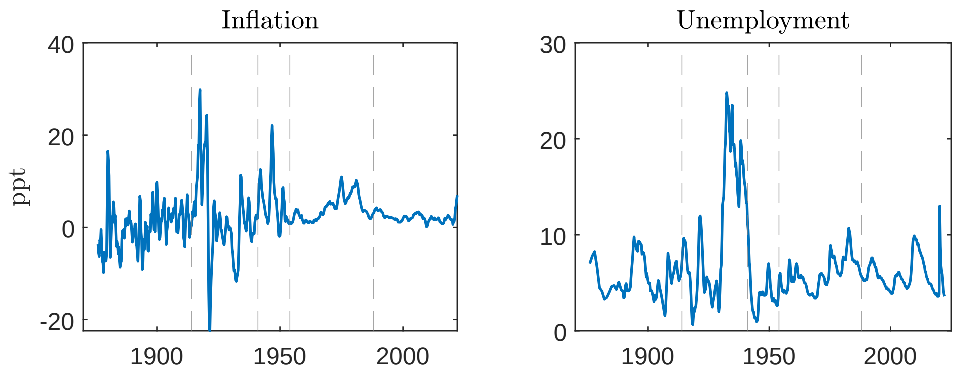
$$
\begin{aligned}
\Delta_{\xi,a} &= \mathrm{Tr}(\Gamma^{0\prime}\mathcal{W}\mathcal{R}_a^0(\mathcal{R}_a^{0\prime}\mathcal{W}\mathcal{R}_a^0)^{-1}\mathcal{R}_a^{0\prime}\mathcal{W}\Gamma^0) \\
&= \mathrm{Tr}(\Gamma_b^{0\prime}\mathcal{W}\mathcal{R}_a^0(\mathcal{R}_a^{0\prime}\mathcal{W}\mathcal{R}_a^0)^{-1}\mathcal{R}_a^{0\prime}\mathcal{W}\Gamma_b^0) + \mathrm{Tr}(\Gamma_{-b}^{0\prime}\mathcal{W}\mathcal{R}_a^0(\mathcal{R}_a^{0\prime}\mathcal{W}\mathcal{R}_a^0)^{-1}\mathcal{R}_a^{0\prime}\mathcal{W}\Gamma_{-b}^0) \\
&\leq \Delta_{ab} + \mathcal{E}_{ab}^0
\end{aligned}
$$

where the inequality follows as $\mathcal{E}_{ab}^0 = \mathcal{L}^0 - \mathrm{Tr}(\Gamma_b^{0\prime}\mathcal{W}\Gamma_b^0) - \mathrm{Tr}(\mathcal{R}_a^{0\prime}\mathcal{W}\mathcal{R}_a^0) = \mathrm{Tr}(\Gamma_{-b}^{0\prime}\mathcal{W}\Gamma_{-b}^0) + \mathrm{Tr}(\mathcal{R}_{-a}^{0\prime}\mathcal{W}\mathcal{R}_{-a}^0)$ and

$$
\mathrm{Tr}(\Gamma_{-b}^{0\prime}\mathcal{W}\mathcal{R}_a^0(\mathcal{R}_a^{0\prime}\mathcal{W}\mathcal{R}_a^0)^{-1}\mathcal{R}_a^{0\prime}\mathcal{W}\Gamma_{-b}^0) \leq \mathrm{Tr}(\Gamma_{-b}^{0\prime}\mathcal{W}\Gamma_{-b}^0) + \mathrm{Tr}(\mathcal{R}_{-a}^{0\prime}\mathcal{W}\mathcal{R}_{-a}^0)\ .
$$

□

Figure 2: Inflation and unemployment, 1879–2019



Notes: Year-on-year inflation (GDP deflator) and the unemployment rate. The vertical lines highlight the different periods: Pre Fed 1879-1912, Early Fed 1913-1941, Post WWII 1951-1984 and Post Volcker 1990-2019.

Table 1: Realized losses

	Pre Fed 1879-1912	Early Fed 1913-1941	Post WWII 1951-1984	Post Volcker 1990-2019
$\mathcal{L}_\pi^0$	24.3	83.0	11.9	0.7
$\mathcal{L}_u^0$	5.7	81.0	6.5	5.8
$\mathcal{L}^0$	30.0	164.0	18.4	6.5

Realized losses for inflation ($\mathcal{L}_\pi$), unemployment $\mathcal{L}_u$ and total ($\mathcal{L}_\pi + \mathcal{L}_u$) for the different periods.

Table 2: Evaluation US Monetary Policy: 1879-2019

Panel (i) Distances to Minimum Loss (DML)

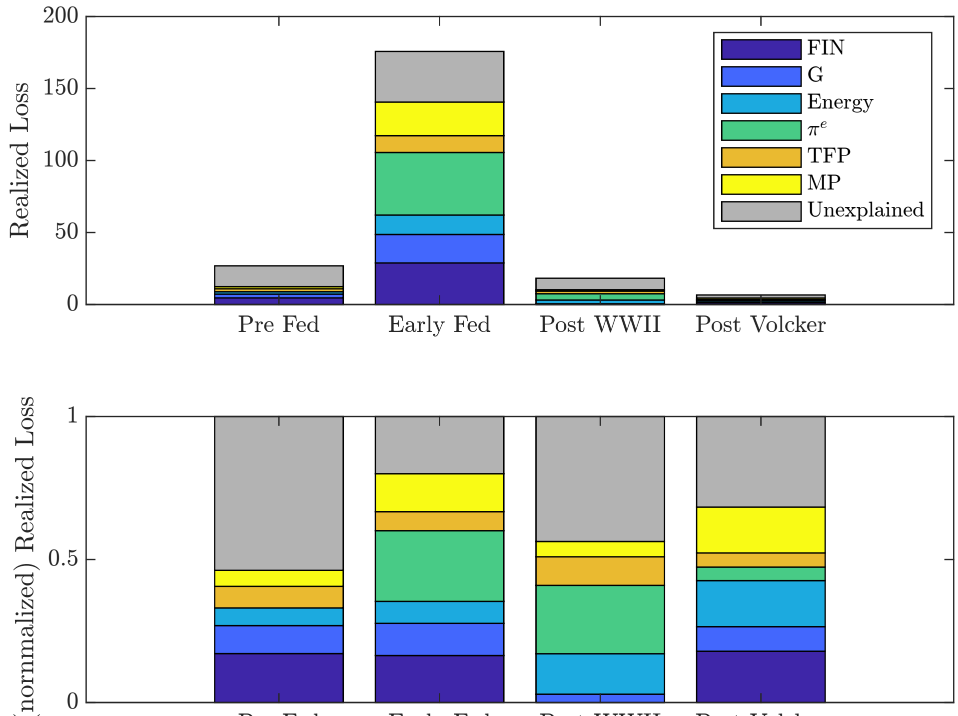
	Δ_{ab}						Δ_a
	Bank panics	G	Energy	π^e	TFP	MP	[lower bound, upper bound]
Pre Fed 1879−1912	**1.5** (0.3,3.5)	**0.6** (0.1,2.1)	**0.2** (0,0.6)	—	**0.6** (0.1,1.7)	**1.5** (0.7,3.2)	**[2.9, 17.3]**
Early Fed 1913−1941	**27.7** (11.5,67.4)	**6.6** (0.8,24.3)	**1.6** (0.1,8.6)	**27.9** (9.4,70.4)	**2.3** (0.2,11.8)	**18.5** (8.8,37.9)	**[66.1, 101]**
Post WWII 1951−1984	—	**0.1** (0,0.8)	**0.9** (0.1,3.5)	**1.7** (0.3,5.5)	**0.4** (0,2.3)	**1.2** (0.4,3.2)	**[3.1, 11.0]**
Post Volcker 1990−2019	**0.1** (0,0.6)	**0.1** (0,0.4)	**0.2** (0,0.9)	**0** (0,0.2)	**0.1** (0,0.4)	**0.7** (0.3,1.9)	**[0.5, 2.6]**

Panel (ii) Optimal Reaction Adjustments (ORA)

	Bank panics	G	Energy	π^e	TFP	Average |ORA|
	$u\uparrow$	$u\uparrow$	$\pi\uparrow$	$\pi\uparrow$	$\pi\uparrow$	
Pre Fed 1879−1912	**−0.9*** (−1.5,−0.3)	**−0.6*** (−1.3,0)	**−0.1** (−0.5,0.4)	—	**0.6** (−0.2,1.1)	**0.6**
Early Fed 1913−1941	**−1.2*** (−1.9,−0.8)	**−0.5*** (−0.9,−0.1)	**0.0** (−0.3,0.3)	**0.7*** (0.3,1.0)	**0.1** (−0.2,0.5)	**0.5**
Post WWII 1951−1984	—	**−0.2** (−0.8,0.3)	**0.8*** (0.1,1.4)	**1.2*** (0.6,1.8)	**0.5** (−0.2,1.2)	**0.7**
Post Volcker 1990−2019	**−0.3** (−0.8,0.2)	**0.1** (−0.4,0.6)	**−0.2** (−0.8,0.7)	**−0.1** (−0.4,0.3)	**−0.3** (−0.7,0.1)	**0.2**

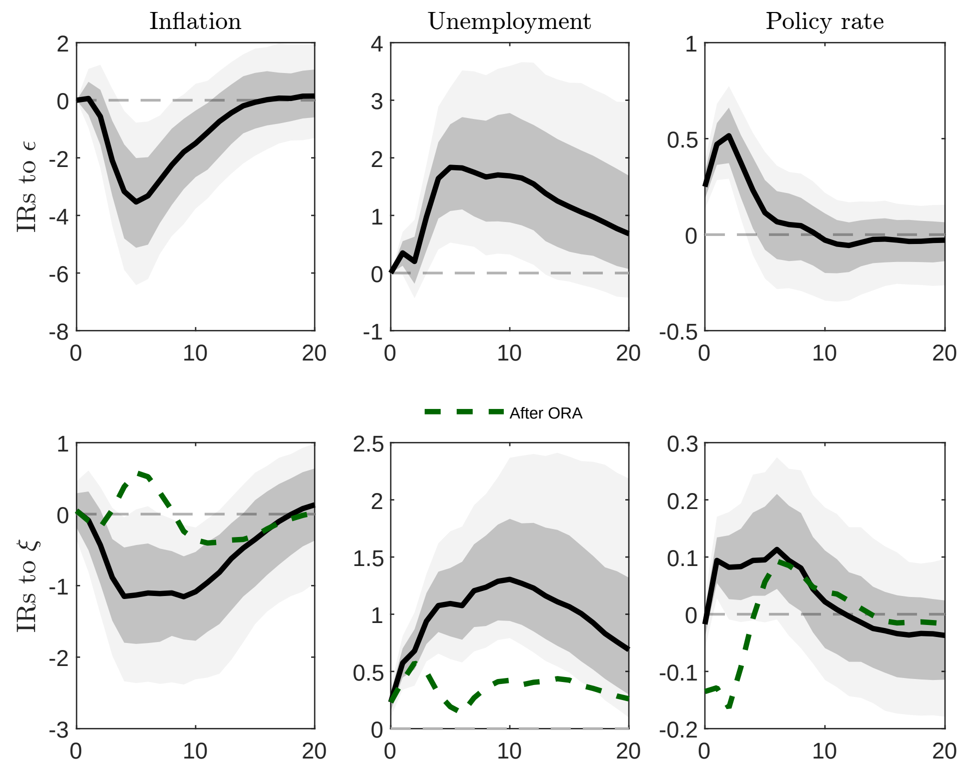
Panel (i) shows median subset distance to minimum loss (DML, Δ_{ab}) together with 68% credible sets with each row and column reporting estimates for a different period and different non-policy shock. The rightmost column reports median estimates for upper and lower bounds for the total distance to minimum loss for the contemporaneous policy rate (Δ_a). Panel (ii) shows median ORA statistics together with 68% credible sets corresponding to different periods and non-policy shocks. The right column ("Average |ORA|") reports the average absolute ORAs estimated for each period. For both panels 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). For the Pre Fed period the TFP, G and Energy DML/ORAs are computed over the 1890-1912 period. The monetary policy shocks (MP) are identified as described in the main text: using gold rush discoveries in the pre-Fed period, Romer and Romer (1989)'s Friedman-Schwartz dates in the early Fed period, Romer and Romer (2004) monetary shocks for the post WWII period and high-frequency surprises in the post Volcker period.

Figure 3: Loss ($\mathcal{L}^0$) decomposition, 1879-2019



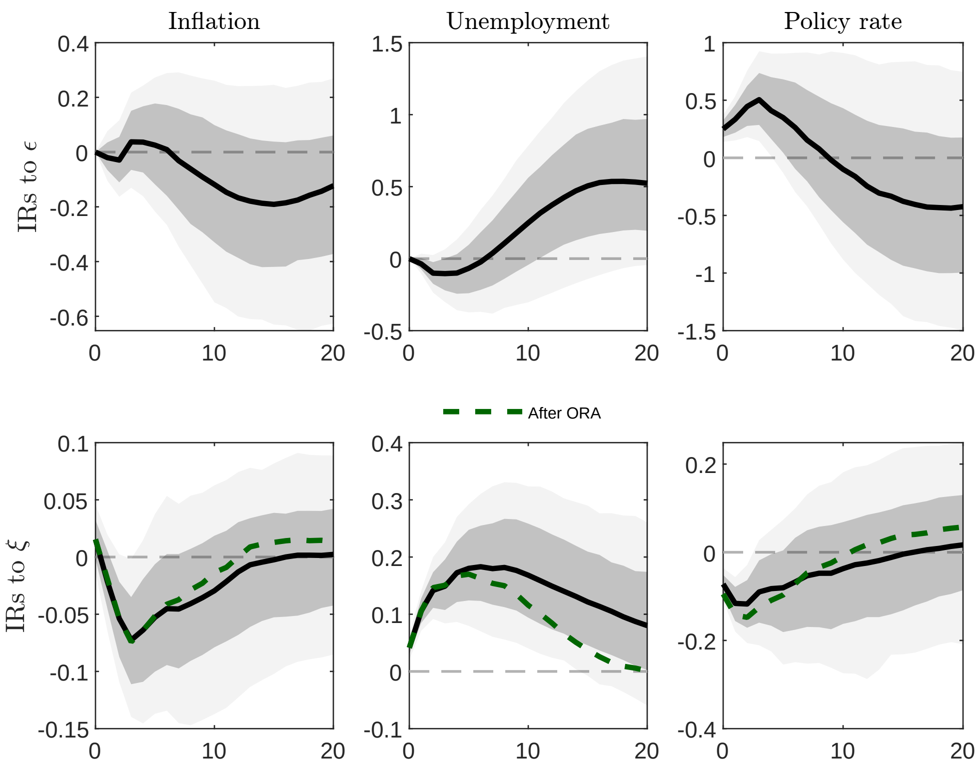
Decomposition of $\mathcal{L}^0$ into the contribution of each identified shock (financial, government spending, energy price, inflation expectation, TFP, monetary policy). The grey shaded area depicts the unexplained part of $\mathcal{L}^0$. The top panel reports decomposition for the level of $\mathcal{L}^0$, while the bottom panel reports the same decomposition but for the level of $\mathcal{L}^0$ normalized on 1 in each period.

Figure 4: Early Fed, 1913-1941, Reaction to Financial shocks



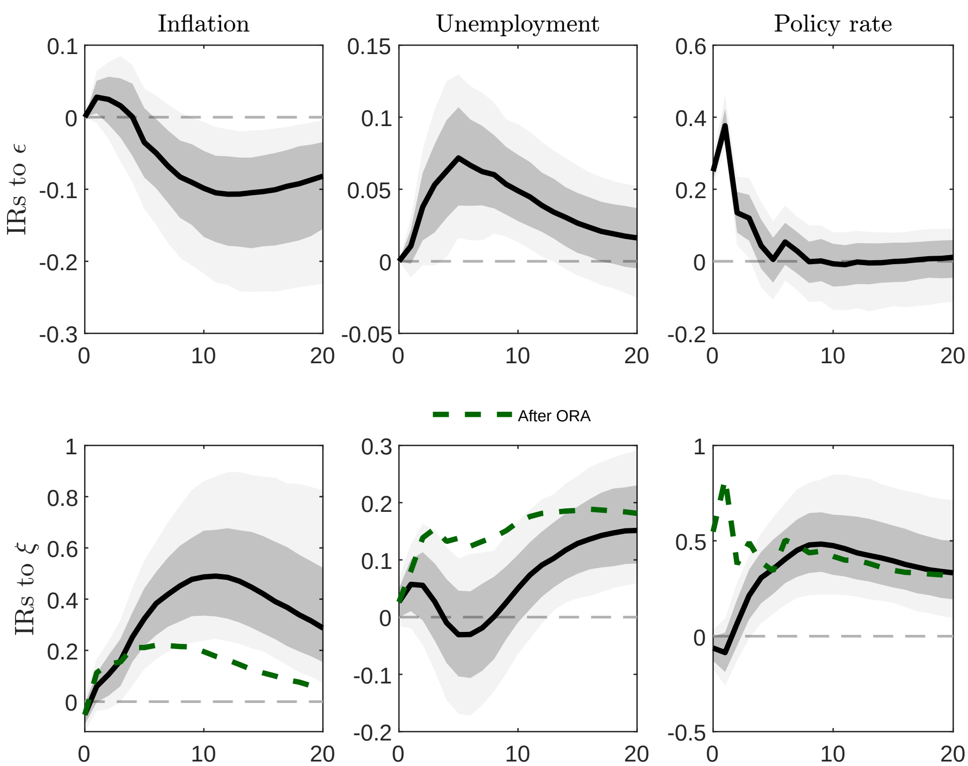
The top (resp. bottom) row shows the median responses (thick line) of inflation, unemployment and the Fed's discount rate to a monetary policy shock ϵ (resp. financial shock ξ). The dotted green lines show the ORA adjusted impulse responses: $\Gamma^0 + \mathcal{R}^0\tau_0^*$. The 95% and 67% credible sets are plotted as dark and light shaded areas, respectively.

Figure 5: Post Volcker Fed, 1990-2019, Reaction to Financial shocks



The top (resp. bottom) row shows the median responses (thick line) of inflation, unemployment and the fed funds rate to a monetary policy shock (resp. financial shock). The dotted green lines show the ORA adjusted impulse responses: $\Gamma^0 + \mathcal{R}^0\tau^*$. The 95% and 68% credible sets are plotted as dark and light shaded areas, respectively.

Figure 6: Post WWII Fed, 1951-1984, Reaction to π^e shocks



The top (resp. bottom) row shows the median responses (thick line) of inflation, unemployment and the fed funds rate to a monetary policy shock (resp. inflation expectations shock). The dotted green lines show the ORA adjusted impulse responses: $\Gamma^0 + \mathcal{R}^0\tau^*$. The 95% and 68% credible sets are plotted as dark and light shaded areas, respectively.