

# The impact of global economies on US inflation: A test of the Phillips curve

Hany Guirguis<sup>1</sup> · Vaneesha Boney Dutra<sup>2</sup> · Zoe McGreevy<sup>3</sup>

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## Abstract

Understanding the relationship between employment and inflation is of great interest to policymakers and market participants. This paper introduces a new global inflation measure based on the principal component analysis (PCA) of the inflation rates of major US trade partners. We find that US domestic inflation correlates strongly with global inflation in the short- and long term. Moreover, global inflation leads the US inflation and accounts for 80% of the price discovery process. Additionally, we show that the Phillips curve equation improves in-sample and out-of-sample forecasting of US inflation rates by incorporating our spill-over-based global inflation (SGI) measure. Also, the utilization of the SGI in the Phillips equation increases the responsivity of the inflation rate data to the unemployment gap by 37%. In summary, the present results support the hypothesis that global inflation is a crucial determinant of domestic (US) inflation. The paper's main findings draw vital policy implications that emphasize the need for stronger cooperation among central banks to cope with the spill-over effect of global inflations on domestic economies.

**Keywords** Global Inflation · Phillips Curve · Price Discovery · Principal Component · Inflation Forecasts

Jel Classification  $C5 \cdot E5 \cdot F6$ 

Hany Guirguis Hany.guirguis@Manhattan.edu

Vaneesha Boney Dutra vboney@du.edu

Zoe McGreevy zmcgreevy01@manhattan.edu

- <sup>1</sup> Ambassador Charles A. Gargano Endowed Chair, O'Malley School of Business, Manhattan College, New York, NY, USA
- <sup>2</sup> Howard University, Washington, DC, USA
- <sup>3</sup> Manhattan College, Bronx, NY, USA

## 1 Introduction

Understanding the relationship between employment and inflation is of great interest to policymakers and market participants. Recent studies have revealed a weakening trend in the traditional relationship between unemployment and inflation wherein a strengthening economy with falling unemployment tends to increase consumer demand, thus causing prices to rise. Potential explanations for the weakened relationship between inflation and economic slack discussed in the literature include non-linearity in the relationship between inflation and unemployment (Albuquerque and Baumann 2017), inaccurate measures of economic slack and inflation (Ball and Mazumder 2019), anchored inflationary expectations (Ball and Mazumder 2019), and globalization effects (Auer et al. 2019). Regardless of the underlying causes, flattening the Phillips curve has driven the US Federal Open Market Committee to re-evaluate its historical strategy of pre-emptive withdrawal of accommodation when unemployment rates drop a natural level.

Motivated by the theoretical models of Clarida et al. (2002) and Martínez-García and Wynne (2010, 2013), we examine the spill-over effect of global inflation on US domestic inflation. First, we introduce a new measure for global inflation based on a principal component analysis (PCA) of the inflation rates of major US trade partners, including China, Canada, Mexico, Japan, Germany, Korea, and the UK. We then test how well our spill-over-based global inflation measure (SGI) correlates with domestic inflation in the short and long term. Finally, we demonstrate how incorporating our SGI parameter into the Phillips curve affects in-sample forecasts, out-of-sample forecasts, and the Phillips curve slope.

The remainder of this paper is organized into Sections 2–5. Section 2 provides a theoretical review of the various explanations for the observed flattening of the slope of the Phillips curve. Section 3 estimates SGI and examines its contribution to the Phillips curve. In Section 4, we report how incorporating the SGI index into the Phillips curve equation affects out-of-sample predictions of the US inflation rate. Finally, in Section 5, a conclusion and policy implications of the analyses are given.

## 2 Theoretical review

Decades of research have questioned the relationship's stability between inflation and unemployment and its validity over time. These studies offer varying theories as to why this relationship may have changed. Some researchers attribute the weakened relationship to the nonlinear relationship between inflation and slack in the economy. Clark et al. (1996) found that when firms have excess capacity during periods of increasing demand, they have little pressure to raise prices. However, during periods of economic overheating when firms are operating close to their total capacity, strengthening demand triggers substantial price increases. Ball and Romer (1991) demonstrated that price rigidity plays a considerable role

in inflation dynamics. For example, when inflation is higher, firms need to adjust price levels more frequently, which is reflected in a steepening of the Phillips curve slope. However, firms are under less pressure to adjust their prices when inflation is low. Thus, weak inflation for prolonged periods obviates the need for frequent price adjustments. Akerlof et al. (1996) have shown that employers prefer to lay off their least productive employees rather than enact wage cuts. Firm managers believe that even nominal wage cuts have a negative impact on morale, which disrupts labor efficiency. Thus, downward labor market adjustments are mediated primarily by unemployment rather than wage reductions. Because of wage rigidity, salary levels within a cycle are inversely related to the depth and length of short-term unemployment. For example, a more profound and extended period of high unemployment will suppress salary augmentation. Xu et al. (2015) observed an asymmetric, nonlinear Phillips curve with a roughly convex shape around the 75<sup>th</sup> quantile, with linearity maintained around the 25<sup>th</sup> quantile. In a subsequent study of the nonlinear behavior of inflation, Albuquerque and Baumann (2017) concluded that the inclusion of nonlinear specifications when generating Phillip's curve could improve the model's performance relative to the standard linear model.

Beyond the nonlinearity of the Phillips curve, several additional concerns have been raised, including the need for more accurate measures of unemployment and economic slack and the effects of anchored inflation and globalization. For the Phillips curve to provide valuable insights, policymakers must employ appropriate economic measures. For example, according to Ball and Mazumder (2019), the impact of economic slack on the labor market in the Phillips equation is better captured with short-term unemployment data than with long-term unemployment data. They argue that those who have been unemployed for more than 27 weeks and are still looking for a job are not competitive or not seriously looking for a job after being unemployed for such a long time. Thus, labor supply may be best reflected by the percentage of short-term unemployed workers in the labor market. For example, during the great recession, inflation did not fall from 2009 to 2011 as had been predicted, partly because short-term unemployment rose less sharply than total unemployment. Coibion and Gorodnichenko (2015) present an alternative explanation in which they explore the idea that firms' inflation expectations are best proxied by household expectations. They posit that an expectations-augmented Phillips curve, following Friedman's (1968) suggestion, utilizing household forecasts presents a more accurate representation of inflation events.

A third explanation for the apparent weakening relationship between employment level and inflation rate hangs on the Federal Reserve anchoring inflation expectations around its 2% target. As a result, inflation has become less responsive to fluctuations in the unemployment gap and the state of the economy. Benati (2008), Gurkaynak et al. (2010), Davis (2012), Davis (2014), and Bundick and Smith (2020) have confirmed that anchored inflation has flattened the slope of the Phillips curve by demonstrating the reduction in the responsiveness of inflation expectations to endogenous and exogenous domestic shocks. In addition, Jorgensen and Lansing (2019) have shown that accounting for anchored inflationary expectations within the

framework of the New Keynesian model improves both the stability of the Phillips curve slope and inflation forecasting substantially.

A fourth possible explanation, which was adopted as the focus of this research, addresses the impact of globalization. Theoretically, the workhorse of the New Open Economy Macro Model (NOEM) introduced by Clarida et al. (2002) and Martínez-García and Wynne (2010, 2013) provides a solid ground for the integration of global inflation in the formation of local inflation. Clarida et al. (2002) derived a two-country open economy version of the dynamic New Keynesian model. The authors show that the reaction function of the central banks should include both domestic and foreign inflation. Further, they show that the magnitude of the response of the domestic central bank to foreign inflation depends on the sign and the relative strength of the spillover of the foreign output gap on domestic marginal cost. Martínez-García and Wynne (2010) Extended Clarida's model by allowing firms to set the prices of their good and services in the importing markets or what is referred to as the local currency pricing (LCP). The structure of their models incorporates three equations: open economy Phillips curve, open-economy IS, and domestic and foreign Taylor rule. Their workhorse New Open Economy Macro model (NOEM) has become the building stone of international macroeconomics. Martinez-Garcia and Wynne concluded that the Phillips curve is getting flattered as the local economies become globalized. Further, they show that the foreign output gap is an essential determinant in the Phillips curve equation. Following Martínez-García and Wynne (2014), Duncan and Martínez-garcía (2015) decompose the NOEM into two subsystems that divide local inflation into its components: global and differential inflation. Next, the authors established that local and international inflations are cointegrated.

The following papers further support the argument for including a measure of global inflation in our Phillips Curve equation. Bonello and Swartz (1978) provide a succinct overview of essays detailing the theory and economic challenges fiscal and monetary policy faces over time. Their summation highlights the notion that internationally, debt-ridden countries threaten to destabilize economies beyond their borders, thus the need to incorporate global measures when examining inflation and other indicators of domestic economic health. Black (1978) examines the impact of international historical shocks and economic disturbances on global economies. Frisch (1977) provides a comprehensive overview of inflationary theories and the Phillips curve for 1963–1975. Also, Bruno (1978) examines pricing dynamics and the price adjustment process and concludes that exchange rates and import prices significantly impact the pricing mechanism. Moreover, they directly note that a twodimensional Phillips Curve may not be sufficient in an open economy and should include alternative measures/dimensions. Also, Cebula and Frewer (1980) analyze, empirically, whether and to what extent there is an 'imported' component to domestic inflation. Specifically, they examine the 'price effect' and whether petroleum prices/imports have contributed significantly to domestic inflation. Finally, they conclude that exogenous, international forces increasingly impact economies of developed nations and that one-way inflation is imported is via petroleum prices and imports.

Recently, Obstfeld (2020) describes the impact of globalization on domestic inflation through the global competitive environment and import pricing channels.

Specifically, Obstfeld posits that the global competitive environment exerts downward pressure on domestic inflation rates by discouraging firms from increasing their prices in response to a higher marginal cost of production. Meanwhile, according to this view (Sbordone 2009), global competition facilitates the US economy's access to global slack within emerging and developing countries, which weakens the bargaining power of the US domestic factor of production, thereby limiting negotiations for higher compensation even when the domestic economy is operating above its potential output. Additionally, the availability of low-priced imported goods affects domestic inflation of both production and consumer goods.

Auer et al. (2017) have demonstrated that the growth of trade in intermediate goods and services has been the driving force of the increasing (decreasing) role of global (domestic) slack in the Phillips curve equation. They attribute this increased importance to expanding global value and supply chains in response to the broad worldwide integration of production processes. Auer et al. (2019) found that globalization could explain 51% of the variance in producer price inflation in a sample of 30 countries. Half of this variance was attributed to the cross-border propagation of cost shocks through international input-output linkages. Similarly, Ciccarelli and Mojon (2010) found that inflation in 22 OECD countries had a common factor accounting for 70% of these countries' inflation variance from 1960 to 2008. Incorporating this common global factor in the inflation equation for the 22 OECD countries improves the out-ofsample forecasting of inflation rates. A wide variety of variables have been incorporated into Phillips' equation in efforts to capture the growing impact of globalization, including global commodity prices, global slack, exchange rates, import and oil prices, the global output gap, and nonlinear exchange rate pass-through (Borio and Filardo 2007; Jašová et al. 2018; and Forbes 2019). These studies demonstrate the importance of globalization in explaining and forecasting domestic inflation while underscoring the diminishing role of domestic slack in explaining inflation rates.

In this paper, we explore the aforementioned inflation commonalities and hypothesize and show that inflation should, at least in part, be modeled as a global rather than a local phenomenon. Our research focuses on the spillover effect of international inflation on US inflation. Specifically, we examine whether incorporating global inflation data into Phillip's curve would accurately represent the relationship between unemployment and inflation.

In sum, these papers lend further credence to our notion that, in a changing environment where there is greater global interdependence, global measures may be critical in examining the inflationary environment.

#### 3 Estimation techniques and empirical results

#### 3.1 Data

#### 3.1.1 Global inflation

We collect quarterly Consumer Price Index (CPI) data on all items for the USA and its leading trade partners (China, Canada, Mexico, Japan, Germany, Korea,

and the UK) from 2003:Q1 to 2019:Q4. We then estimate each country's inflation rate (percentage) from the previous year. Descriptive statistics for the annualized quarterly inflation rates are shown in Table 1, and US inflation rates are plotted against the inflation rates of its main trade partners in Fig. 1. Average inflation rates for US trade partners vary from 4.08% (Mexico) to 0.257% (Japan). Notably, China exhibits the most highly variant inflation rate, fluctuating between 7.78% and -1.54%, with a standard deviation of 1.84%. Germany, which shows the second-lowest average inflation rate of 1.42%, has the most stable domestic prices with a standard deviation of only 0.68%. Jarque–Bera statistics show that inflation in China, Canada, Mexico, and Japan do not follow a normal distribution. The US inflation rate correlates strongly with inflation rates in Germany (r=0.80), Canada (0.68), China (0.60), Korea (0.53), and UK (0.52), but not with inflation rates in Japan (0.17) and Mexico (0.03) (see Table 1 and Fig. 1).

Consistent with the work of Bernanke et al. (2005), we use PCA to create our SGI, an independent composite factor representing global inflation. We apply PCA to the inflation rates in China, Canada, Mexico, Japan, Germany, Korea, and the UK, keeping the first principal component as our proxy variable for global inflation and find that the US inflation rate and our global inflation index SGI are strongly correlated in the short run, with a correlation coefficient of 0.79 (Fig. 2).

We then test for long-term correlation and price discovery between domestic inflation and the global inflation index with Johansen's (1988) cointegration test and Hasbrouck's (1995) price discovery technique. Johansen (1988) introduced a full-information maximum likelihood technique that enables simultaneous estimation of the long-run equilibrium relationship and short-term linkages, where the results do not depend on which variable is dependent. Following Johansen and Juselius (1990), let us consider a vector  $X_t$  of p non-stationary I(1) series. Such a series has the following vector autoregressive representation (VAR):

$$X_{t} = A_{1}X_{t-1} + \dots + A_{n}X_{t-n} + \varphi D_{t} + \varepsilon_{t}, t = 1, \dots, T,$$
(1)

Nation	Min	Mean	Max	SD	Skew	Kurt	JB	Correlation with US rate
USA	-1.6200	2.0683***	5.1192	1.2079	-0.3563	1.0332*	4.4629	1.0
China	-1.5429	2.5577***	7.7855	1.8042	0.8283***	1.3404**	12.8667***	0.60
Canada	0.1758	1.6521***	3.8766	0.7322	$0.5058^{*}$	0.1445***	$2.9586^{***}$	0.68
Mexico	2.2489	4.0810***	6.3856	0.9288	$0.5429^{*}$	0.1096***	3.3749***	0.03
Japan	-2.2381	$0.2578^{**}$	3.5378	1.0017	$0.8942^{***}$	2.4866***	26.5818***	0.17
Germany	-0.2353	1.4205***	3.0342	0.6874	-0.0028	0.3373	0.3223	0.80
Korea	0.0445	2.2777***	5.3932	1.2138	0.3081	-0.5981	2.0895	0.53
UK	0.3333	2.0813***	4.3826	0.8727	0.2285	0.2831	0.8186	0.52

 Table 1
 Descriptive statistics for CPI inflation rates (2003:Q1–2019:Q4)

All series are annualized quarterly inflation rates for the study period. The null hypothesis for the Jarque– Bera (JB) test is that the data are normally distributed. The null hypotheses for mean, skew, and kurt are that the statistics are not statistically different from zero. \*, \*\*, \*\*\* denote significance at 10%, 5%, and 1% levels, respectively. CPI, Consumer Price Index; SD, standard deviation



**Fig. 1** CPI of inflation for the USA and main US trade partners. Annualized quarterly inflation rates are shown from 2003:Q1 to 2019:Q4. The y axes represent inflation rate. The x axes represent time from 2003 through 2019

where  $X_t$  is a (p×1) vector of I(1) non-stationary p time series, T is the number of observations, n is the number of lags, and  $D_t$  values are centered seasonal dummies that sum to zero over the entire sample period. If all of the time series in the VAR have a single unit root that can be removed by taking the first difference, then the VAR can be expressed as



**Fig. 2** US inflation versus global inflation. The graph shows the US inflation and an index for global inflation based on the first principal component of the inflation rates in China, Canada, Mexico, Japan, Germany, Korea, and the UK. The left axis represents the inflation rate, the right y-axis represents the values of the index of global inflation, and the x-axis represents the time from 2003 through 2019

$$\Delta X_t = \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{n-1} \Delta X_{t-n+1} + \varphi D_t + \varepsilon_t, \tag{2}$$

where

$$\Pi = \sum_{i=1}^{n} A_i - I_p \text{ and } \Gamma_i = -\sum_{i=i+1}^{n} A_i$$

In this framework, the cointegration hypothesis can be tested by evaluating the rank of the long-run impact matrix ( $\Pi$ ). More specifically, the number of distinct cointegrating vectors, r, is equal to the rank of  $\Pi$ , or the number of characteristic roots of  $\Pi$  that are statistically different from zero. As stated by Juselius (2006), "If  $X_t$  is ~I(1), then  $\Delta X_t$  is stationary and can't be written in terms of the non-stationary variable  $\Pi X_{t-1}$ . Therefore,  $\Pi$  can either be zero or it must have the reduced rank ( $\alpha\beta'$ )", where  $\alpha$  and  $\beta$  are the p×r matrices of the speed of adjustment parameters and the cointegrating parameters respectively, and r is the number of cointegrating relationships (0 < r < p). Accordingly, Eq. (2) can be written in terms of the error correction feature ( $\alpha\beta' X_{t-1}$ ) and the VAR to form the vector error correction model as follows:

$$\Delta X_t = \alpha \beta X_{t-1} + \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{n-1} \Delta X_{t-n+1} + \varphi D_t + \varepsilon_t, \tag{3}$$

Price discovery describes how the information for a particular asset is transmitted among different markets in which the asset is traded. Generally, the efficient markets hypothesis requires that asset information be reflected quickly and fully in asset pricing. Moreover, since the introduction of modern portfolio theory in the 1950s-wherein mean-variance analysis is used to assemble a portfolio designed to maximize return for a given level of risk-academics and practitioners have been keen to better understand price discovery and the co-movement of different types of assets in order to better predict the magnitudes of benefit for particular diversification schemes. Barkham and Geltner (1995) point out that price discovery can happen first in the unsecuritized market due to the larger market size and trading volumes. More informed and specialized investors conduct trades. The estimated speed of adjustment parameters,  $\alpha$ , can then be utilized to examine price discovery in the different markets. For example, suppose all adjustment parameters are statistically significant with the correct sign for stability. In that case, none of the markets are weakly exogenous, and the adjustment process to restore equilibrium will take place in all the markets. In this case, the relative magnitude of the coefficients will determine which market leads in terms of price discovery. Conversely, suppose  $\alpha$  is statistically significant only in the first market. In that case, the price discovery occurs in the other markets, and the first market adjusts to remove the disequilibrium in the long-term relationship.

In our paper, we utilize Hasbrouck's (1995) technique to estimate the share of each market in price discovery. First, Hasbrouck presents  $\Delta X_t$  in Eq. (3) by the following vector moving-average:

$$\Delta X_t = \Psi(L)\varepsilon_t,\tag{4}$$

where  $\Psi(L)$  is a polynomial in the lag operator. When X attains its long-term equilibrium value (X\*), Eq. (3) can be written as follows:

$$X^* - X_{t-1} = \Psi(1)[\varepsilon_t] = \sum_{i=0}^{\infty} \Psi_i[\varepsilon_t] = \theta \Psi[\varepsilon_t] = \beta_{\perp} \alpha'_{\perp}[\varepsilon_t],$$
(5)

where  $\beta_{\perp} \alpha'_{\perp} \epsilon_t$  is the long-term effect of the innovations of n markets. Additionally, the variance of  $\theta \Psi \epsilon_t$  is  $\Psi \Sigma \Psi'$  under the assumption that p markets respond identically to innovations in efficient prices in the long-run.

In accordance with the work of Hasbrouck (1995), we decompose  $Var(\theta \Psi \varepsilon_i)$  into its n components  $(v_i^2)$  attributable to each market and then derive a Cholesky decomposition of  $\Sigma$  in terms of F, where  $\Sigma = FF'$ , and calculate  $V_i^2$  as follows:

$$V_i^2 = ([\Psi F]_i)^2$$
(6)

The share of each market in price discovery  $(S_i)$  is then calculated by dividing  $V_i^2$  by the total innovation variance as follows:

$$S_i = \frac{V_i^2}{\Psi \Sigma \Psi'} = \frac{\left([\Psi F]_i\right)^2}{\Psi \Sigma \Psi'} \tag{7}$$

We commence empirical testing by examining the classical assumption of the non-stationarity of our series. To do so, we utilize the Dickey-Fuller unit root test, wherein the number of lags is determined by the Akaike information criterion. As illustrated by Table 2, we find that taking the first difference of each series results in the removal of one-unit root from US inflation and global inflation rates (5% significance level).

We then perform Johansen's cointegration trace test between US inflation and global inflation. To determine the stability of the underlying long-term relationships among the series, we run Johansen's test iteratively over the samples with forward estimation. The first subsample for forward estimation is from 2003:Q1 to 2013:Q1, and the last (full) sample runs from 2003:Q1 to 2019:Q4 (36 iterations). Finally, for each two-series set that is cointegrated, we run the Hasbrouck (1995) test and calculate the contribution of each set to the process of price discovery.

The trace test for foreword interactions confirms a strong cointegration relationship between domestic and global inflation rates in forward-rolling estimates. The contribution of each inflation series to price discovery when two sets are cointegrated can be

Parameter	Minimum AIC lags	Dickey-Fuller constant	
US inflation rate			
Level	5	-2.5707	
First difference	7	-4.7584***	
Global inflation index			
Level	8	-1.3980	
First difference	7	-5.4354***	

Data reflect US inflation rate stationarity, the global inflation index, and their first difference. \*, \*\*, \*\*\* denote significance at 10%, 5%, and 1% levels, respectively. AIC, Akaike information criterion

Table 2Dickey-Fuller unit roottests

seen in Fig. 3, which shows cointegration of the two-time series in all the forward tests and illustrates the dominance of a global inflation index. Notably, the average statistics for all forward-rolling estimates show that global inflation leads US inflation and accounts for 80% of price discovery. In summary, our analysis confirms strong short-and long-term relationships between global inflation and US domestic inflation.

## 3.1.2 Phillips curve and global inflation

This section examines the impact of accounting for global inflation on the performance of the Phillips curve equation. We follow Laubach and Williams's specifications (2003) to estimate an augmented Phillips curve. However, we replace the core PCE with the CPI as our inflation rate measurements. The other determinants in the CPI inflation ( $\pi_{CPI}$ ) equation are the expected inflation ( $\pi_{CPI}^e$ ), output Gap ( $\tilde{y}$ ), crude



### A) Trace test of cointegration

**Fig. 3** Forward rolling trace test and Hasbrouck test results. **A.** Forward rolling trace test for cointegration (y axis) between US inflation and global inflation (solid line); the 95% critical value is shown with a dotted line. **B.** Hasbrouck test outcome for subsamples starting on 2003:Q1 and ending from 2013:Q1 to 2019:Q4. The y axis represents percent contribution to price discovery of US inflation (solid line curve) and of global inflation (broken line curve). Subsample end dates are shown on the horizontal axis

 Table 3 Regression results from reduced-form specifications of

the Phillips curve

imported oil inflation gap ( $\pi_{oil} - \pi_{PCE}^{e}$ ), Core import (excluding petroleum, computers, and semiconductor), inflation gap ( $\pi_{import} - \pi_{PCE}^{e}$ ), three moving average inflation ( $MA3\pi_{CPI}$ ), and five moving average inflation ( $MA5\pi_{CPI}$ ). We also use a time trend (D<sub>1</sub>) and a dummy that takes the value of one for 2008:Q1–2009:Q3 and zero elsewhere. Thus, the first specification of the Phillips curve can be stated as follows:

$$\pi_{CPI,i} = \beta_1 + \beta_2 \tilde{y}_{i-1} + \beta_3 \pi_{CPI,i}^e + \beta_4 MA3 \pi_{CPI,-2} + \beta_5 MA5 \pi_{CPI,-5} + \beta_6 (\pi_{oil} - \pi_{CPI}^e)_{i-1} + \beta_7 (\pi_{import} - \pi_{CPI}^e)_{i-1} + \beta_8 D_1 + \beta_9 D_2 + \mu_{1i}$$
(8)

where the output gap is the difference between the unemployment rate (U3) and the natural rate of unemployment published by the congressional budget office. Meanwhile, the expected inflation at time t is the average of the four-step out-of-sample forecasts calculated from regressing inflation on a constant and three lags of the inflation rate. Next, we account for the spillover effect of global inflation by including the first principal component of global inflation rates in the Phillips equation as follows:

$$\pi_{CPI,t} = \gamma_{1} + \gamma_{2} \bar{y}_{t-1} + \gamma_{3} \pi_{CPI,t}^{e} + \gamma_{4} MA3 \pi_{CPI,t-2} + \gamma_{5} MA5 \pi_{CPI,t-5} + \gamma_{6} (\pi_{oil} - \pi_{CPI}^{e})_{t-1} + \gamma_{7} (\pi_{import} - \pi_{CPI}^{e})_{t-1} + \gamma_{8} D1 + \gamma_{9} D2 + \gamma_{10} (globalinflation)_{t-1} + \mu_{3t}$$
(9)

We then apply the ordinary least squares technique to estimate the two specifications for the entire sample from 2003:Q1 to 2019:Q4 and then correct the ordinary least square regressions for autocorrelation and heteroscedasticity using the Newey and West (1987) method. Both regressions are reported in Table 3. Comparing the results that we obtain with and without augmentation of the Phillips equation with our global inflation index, namely SGI, reveals that the

Dependent variable	$\pi_{CPI}$	$\pi_{CPI}$	
R. <sup>2</sup> _adjusted	0.6191	0.7131	
Constant	6.5487**	11.9694***	
$\tilde{y}_{t-1}$	-0.1913***	-0.2629***	
$\pi^e_t$	0.1666	-0.3194	
$MA3\pi_{t-2}$	-0.1274	-0.4788	
$MA5\pi_{t-5}$	-0.0240	-0.0002	
$(\pi_{oil} - \pi^e)_{t-1}$	0.0251**	$0.0186^{**}$	
$(\pi_{import} - \pi^e)_{t=1}$	0.0076	-0.2394**	
D <sub>1</sub>	-0.0169*	-0.0318***	
$D_2$	-0.4176	-0.8768***	
Global_Inflation <sub>t-1</sub>	-	4.6509***	

Regression results for the two specifications utilized in estimating the Phillips curve are shown with the adjusted R-squared statistic and estimated coefficients. \*, \*\*, \*\*\* denote significance at 10%, 5%, and 1% levels, respectively, based on the Newey-West covariance matrix augmentation has three notable effects: (1) increasing the adjusted  $R^2$  value by 15%, from 0.61 to 0.71; (2) increasing the absolute value of the slope of the Phillips curve by 36.8%, from -0.19 to -0.26; and (3) global inflation spillover has a positive effect on US inflation significant at the 1% level.

To examine the stability of the superior performance of the second specification, we calculate adjusted  $R^2$  values, in-sample stability, and estimated coefficients of global inflation, output gap, and their p-values over 27 forward-rolling subperiods starting on 2003:Q1 and ending from 2013:Q1 to 2019:Q4.

The results confirm the superior performance of the Phillips curve specification augmented by the global inflation index as shown in Figs. 4 and 5. Additionally, the slope of the Phillips curve is statistically significant at the 5% level between 2014:Q4 and 2015:Q3 only when global inflation is incorporated in the Phillips equation. Notably, from 2014:Q4 to 2015:Q3, there is an observable divergence of the stronger economies in the USA and UK from the stagnant economies in Japan and Eurozone countries.



**Fig. 4** Forward rolling Phillips curve analysis. **A.** Graph of estimated coefficients of global inflation. **B.** Graph of p-values of the estimated coefficients in the graph shown in panel A. **C.** Graph of output gap values between the estimated coefficients for specification I (solid line) and specification II (dotted line). **D.** Graph of p-values from forward rolling tests of subsamples starting on 2003;Q1 and ending from 2011;Q1 to 2019;Q4. In B and D, data for specification I and II are shown with broken and solid lines, respectively. In C and D, the dash-dot lines represent 1% (lower) and 5% (higher) significance levels



**Fig. 5** Primary comparison of the performance of specifications I and II. **A.** Graph of adjusted R.<sup>2</sup> values calculated from forward rolling regressions of specification I (dotted line), which is generated by a Phillips equation based on the US CPI, and of specification II (solid line), which is generated by a Phillips equation based on the US CPI as well as an augmentation with the presently developed SGI index of global inflation. **B.** Graph of in-sample forecast data generated by specification I (dotted line) and specification II (solid line), together with a plot of the CPI (dashed line) for the same time period. In both graphs, subsamples start on 2003:01 and end from 2011:Q1 to 2019:Q4

The stagnant economies in the Eurozone and Japan decreased the inflation rates in these countries, which put downward pressure on the US inflation rate and weakened its relationship with the output gap. In conclusion, accounting for the spillover effect of global inflation on US inflation in the Phillips equation stabilizes the slope of the Phillips curve, as captured by the second specification.

#### 4 Out-of-sample predictions and properties of the prediction errors

The accuracy of inflation forecasts is limited by inconsistencies across forecasting techniques and model specifications. In their review of forecasting models and comparative analysis of the performance of Phillips curve forecasting specifications, Stock and Watson (2010) find that a univariate forecasting model tends to outperform more complex multivariate models. Alvarez-Diaz and Gupta 2016 subsequently replicated this outcome. Abdelsalam (2017), who notes inherent specification issues that can impact the predictive power of Phillips curves and analyses of augmented versions of Phillips equations that incorporate time-varying coefficients, finds that augmentations can improve forecast accuracy. Gupta et al. (2017) have shown that a factor augmented-qualitative VAR can outperform other augmented VAR models. Furthermore, Balcilar et al. (2017) have demonstrated that the VARFIMA (vector autoregressive fractionally integrated moving average) model is superior to the standard model.

A quick review of the literature indicates that there may not be a one-size-fits-all model or specification. Stock and Watson (2010) make a valid argument that this variability in utility should not be surprising given the fluctuations in US inflation dynamics that have accompanied a transforming US economy and changes in monetary policy regimes. To that end, Inoue et al. (2017) find significant evidence that a forecasting model's performance can be sensitive to estimation window size. They propose a methodology for determining an optimal estimation period that minimizes conditional mean square forecasting error (MSFE). They show that their window selection method deteriorates for models containing numerous predictors with parameters with differing time-varying patterns. They find that an unemployment-based Phillips curve has inflationary predictive power when optimal sizes are used.

To examine the effect of global inflation on an out-of-sample forecast of the US inflation rate, we conduct one-step predictions based on rolling window regressions. First, estimated coefficients from each regression are used to predict the inflation rate of the next quarter in the forward estimation period, with the first subsample being from 2003:Q1 to 2013:Q1, and the last (total) sample running from 2003:Q1 to 2019:Q3. This process generates 27 out-of-sample predictions (Fig. 6) for each model.

Following Clapp and Giaccotto's (2002) approach, we evaluate model performance according to three criteria: the desirability of prediction error properties, the relative efficiency of predictions, and the informational efficiency of projections. A desirable property for forecasting errors is that they show a normal distribution around zero with constant variance. The tendency of a model to overpredict (under-predict) can be detected by a left (right) skewed distribution with a statistically significant negative (positive) mean. Highly inaccurate forecasts can result in excessively negative kurtosis.

We test for relative efficiency by calculating Theil's  $U^2$  value, mean forecasting error (MFE), mean absolute forecasting error (MAFE), and root means squared forecasting error (RMSFE) for 27 forecasts, as follows:

$$U^{2} = 1 - \frac{\sum_{i=1}^{27} (Inflation_{i} - Inflation_{i}^{e})^{2}}{\sum_{i=1}^{27} (Inflation_{i} - \overline{Inflation})^{2}},$$

$$MFE = \sum_{i=1}^{27} \frac{1}{27} ((Inflation_{i} - Inflation_{i}^{e}),$$

$$MAFE = \sum_{i=1}^{27} \frac{1}{27} ((|Inflation_{i} - Inflation_{i}^{e}|), \text{ and}$$

$$RMSFE = \sqrt{\sum_{i=1}^{27} \frac{1}{27} (Inflation_{i} - Inflation_{i}^{e})^{2}}$$

$$(10)$$



**Fig. 6** Graph of out-of-sample forecasts of the US inflation rate. The inflation rate forecasts (x axis) are calculated from the forward rolling regression of specification I (dotted line) and specification II (dashed line). The specification forecast plots are overlain on a plot of the US CPI (solid line). The subsamples start on 2003:01 and end from 2011:01 to 2019:04 (y axis is time). Specifications I and II are as defined as in Fig. 5

where a Theil's  $U^2$  value close to one indicates that the equation can effectively predict future values of the dependent variable, and a negative Theil's  $U^2$  value suggests that the naive specification outperforms forecasts of the equation. To test whether our forecasts are informationally efficient, we first regress the inflation rate on its prediction and a constant term, as follows:

$$Inflation_i = \beta_0 + \beta_1 Inflation_i^e + \varepsilon_i \tag{11}$$

To explore the source of inefficiency or the forecast error, if any, we calculate the mean squared forecasting error (MSPE) based on our estimates from Eq. (11), as follows:

$$MSPE = \left(\overline{inflation^{e}} - \overline{inflation}\right)^{2} + \left(1 - \widehat{\beta}_{i}\right)^{2} VAR(inflation^{e}) + \frac{ESS}{n}$$
(12)

where  $(\overline{inflation^e} - \overline{inflation})^2$ ) refers to the average actual and forecasted series, n is the number of observations,  $\hat{\beta}_i$  is the estimated coefficient, and ESS is the sum of squared forecasting errors. We then calculate Theil's decomposition of the MSPE by dividing Eq. (12) by the MSPE, as follows:

$$\frac{MSPE}{MSPE} = \frac{\left(\overline{inflation^e} - \overline{inflation}\right)^2}{MSPE} + \frac{\left(1 - \hat{\beta}_i\right)^2 VAR(inflation^e)}{MSPE} + \frac{ESS}{MSPE*n} + 1 = U^{bias} + U^{Regression} + U^{error}$$
(13)

where U<sup>bias</sup> is a measure of the bias in  $\beta_0$ , U<sup>regression</sup> is a measure of the bias in  $\beta_1$ , and U<sup>error</sup> is a measure of the portion of the forecast errors that can be attributed to equation residuals. Informational efficiency requires that  $\hat{\beta}_0$  and  $\hat{\beta}_i$  be statistically consistent with zero and one, respectively. If so, the bias will be captured predominantly by U<sup>error</sup>, which should be close to one.

As reported in Table 4, the two models produce normally distributed forecasting errors with means that are statistically different from zero at the 5% percent level. There are several parameters by which specification II (CPI with SGI index of global inflation) outperforms specification I (CPI). Relative to specification I, specification II yield a smaller standard deviation of forecasting errors, exhibits less overshooting with the minimum, and produces more accurate forecasts, as indicated by smaller MAFE, MAFE, and RMFSE values.

Note that a negative Theil's  $U^2$  value is obtained for specification I, indicating that the specification fails to forecast its inflation rate (Table 4). Notably, the second specification has a positive Theil's  $U^2$  value, which indicates that it outperforms the forecasts generated by the naïve model. Additionally, Theil's decomposition of MSPE shows that 73% (47%) of the MSPE in specification I (Specification II) can be attributed to  $U^{\text{bias}}$  and  $U^{\text{regression}}$ . Thus, Theil's decomposition confirms the superiority of specification II, with the component of the MSPE value being attributed to  $U^{\text{error}}$  is 53% for specification II but only 29% for specification I. The superior performance of specification II is further confirmed in the out-of-sample forecast plots shown in Fig. 5. Thus, our forecasts indicate that accounting for spillover effects of global inflation in the Phillips equation improves out-of-sample forecasting of the Phillips curve for the US inflation rate.

Parameter	Specification I: CPI only	Specification II: CPI and SGI
Desirable properties of forecasting errors		
Mean	-0.4512***	-0.2849**
Standard deviation	0.8097	0.6676
Minimum	-2.0871	-1.7268
Maximum	0.9087	0.9794
Skewness	-0.5557	-0.1654
Excess kurtosis	-0.7752	-0.1822
Jarque–Bera	2.0658	0.1604
Relative efficiency		
U. <sup>2</sup> statistic	-0.5429	0.0568
MFE	-0.4512	-0.2849
MAFE	0.6640	0.5789
RMFSE	0.9137	0.7144
Informational efficiency, Theil's decompo-	sition of MSPE	
U. <sup>bias</sup>	0.2870	0.1634
U. <sup>regression</sup>	0.4280	0.3114
U. <sup>error</sup>	0.2850	0.5252

 
 Table 4
 Desirable properties, relative efficiency, and informational efficiency of forecasting errors from CPI Phillips equations

The Table presents means, standard deviations, maximum, minimum, skewness, excess kurtosis, Jarque-Bera normality test, Theil's  $U^2$ , mean forecasting error (MFE), mean absolute forecasting error (MAFE), and root mean squared forecasting error (RMSFE), and Theil's Decomposition of MSPE of the 27 onestep forecasting errors calculated from rolling window regressions. CPI, Consumer Price Index; SGI, spill-over based global inflation measure

## 5 Conclusion

This paper explores the effects of a new measure for global inflation on domestic inflation in the USA. This new measure, termed SGI, is a PCA-based independent composite factor representing global inflation. The SGI exhibits stable and robust short- and long-term correlations with the domestic inflation rate in the USA. The global inflation variable leads the US inflation rate and contributes on the average 80% to price discovery. Incorporating the SGI variable improves the in-sample overall fit by 14.5% and increases the Phillips curve slope by 37%. Furthermore, accounting for spillover effects from global inflation dynamics in the Phillips equation improves out-of-sample forecasting of the Phillips curve for the US inflation rate.

There are many policy implications of the current research. First, globalization can potentially explain the coincidence of solid growth and low inflation before the COVID-19 recession despite the US economy operating around its potential level. Thus, these results support the recent changes in the Federal Reserve's Statement on

Longer-Run Goals and Strategy, which call for abandoning the longstanding principle of reducing accommodation preemptively when the unemployment rate nears its natural rate. Second, the presently documented spillover phenomenon indicates that US monetary policy should respond to global inflation in the economies of its primary trade partners. Thus, strong coordination among major central banks is vital for local and international inflation stability. Third, the social and economic cost of restoring domestic inflation to its long-term goals could increase as the domestic economy is more responsive to global exogenous shocks.

#### Declarations

**Competing interests** Authors are required to disclose financial or non-financial interests that are directly or indirectly related to the work submitted for publication. Please refer to "Competing Interests and Funding" below for more information on how to complete this section.

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