Trade Exposure and the Evolution of Inflation Dynamics

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Abstract

Reasons for the striking attenuation of the relationship between inflation and resource utilization that has been observed in the United States over the past several decades are often linked to the increase in global economic integration. In this paper, we examine this "globalization" hypothesis using both aggregate data on measures of inflation and economic slack and a rich panel data set containing producer prices, wages, output, and employment at a narrowly defined industry level. Our results indicate that the rising exposure of the U.S. economy to international trade can indeed help explain a significant fraction of the overall decline in responsiveness of aggregate inflation to fluctuations in economic activity. This flattening of the Phillips curve is supported strongly by our cross-sectional evidence, which shows that increased trade exposure significantly attenuates the response of inflation to fluctuations in output across industries. Our estimates indicate that the inflation-output tradeoff is three to four times larger for low trade intensity industries compared with their high trade intensity counterparts.

JEL Classification: E30, E31, E32
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1 Introduction

The Phillips curve—the relationship between inflation and fluctuations in economic activity—is a central building block of economic models that allow for nominal rigidities and are relied upon by central banks around the world to gauge cyclical inflationary pressures. The lack of deflationary pressures during the Great Recession and, more recently, the apparent lack of inflationary pressures during the recovery have brought into the forefront the question of whether this relationship still exists in the data.[1] More generally, the fact that inflation appears to have become less responsive to fluctuations in output in employment during the past couple of decades has been documented for the United States by Roberts (2006); this so-called flattening of the Phillips curve appears to have occurred in other advanced economies as well (see Beaudry and Doyle (2000) for Canada and Kuttner and Robinson (2010) for Australia, for example).

Reasons for the apparent attenuation of the relationship between inflation and resource utilization are often linked to the rise in globalization, an increase in the cross-border movement of goods, services, technology, labor, and capital since the 1990s. The resulting greater openness of national economies implies that a greater share of an increase in domestic demand is satisfied through imports, rather than domestic production. In turn, this implies than an increase in the output gap will have a smaller effect on domestic marginal costs, thereby reducing the responsiveness of domestic inflation to changes in economic slack. Increased international trade also gives rise to a common component for inputs such as commodities, implying that local costs—and hence prices—become less sensitive to domestic economic conditions. Increased openness of labor markets should also diminish the link between inflation and economic activity at the local level.[2]

Although prominent in recent policy discussions, the evidence in favor of a weakening in the relationship between inflation and economic activity is mixed. Ball (2006) argues that there is no evidence to suggest that increased trade and globalization attenuates the relationship between inflation and economic slack. Forbes (2018), on the other hand, shows that global factors play a more prominent role in determining U.S. inflation outcomes, but that global factors are primarily linked to the food and energy component of consumer prices and play a diminished, rather than an increased, role in explaining movements in the core measures of consumer price inflation. Notably, neither of these studies provides direct evidence on how trade exposure—a commonly used proxy for globalization—influences the relationship between inflation and fluctuations in economic activity.

In this paper, we re-examine these issues using both U.S. aggregate data on measures of inflation and economic slack and a rich panel data set containing producer prices, wages, output, and employment at a narrowly defined industry level. Industries in our data set are defined at the 6-digit North American Industry Classification System (NAICS) level, and the data on prices and output serve as the basis for the construction of the U.S. producer price index published by the

[1]Recent work that studies the unusual inflation dynamics during the Great Recession and its aftermath in the United States and other advanced economies includes Stock and Watson (2010b), Ball and Mazumder (2011, 2018), Gordon (2013), Friedrich (2016), Berganza et al. (2016), Miles et al. (2017), and Blanchard (2018).

[2]See Bernanke (2007) for an overview of the various channels through which ongoing global economic integration can affect inflation dynamics.

Bureau of Labor Statistics and the industrial production index published by the Federal Reserve Board. We also measure trade exposure at the industry level—albeit at a somewhat coarser level of aggregation (i.e., 4-digit NAICS)—using information on exports, imports, and value-added output. Linking these trade exposures to industry-level prices, wages, employment, and production allows us to directly determine the extent to which the response of inflation to fluctuations in output differs systematically across industries that are more or less exposed to international trade.

We begin our analysis by examining the time-series relationship between inflation and economic activity. We first document that the negative relationship between aggregate inflation—at both the producer and consumer levels—and economic slack occurs primarily in economic booms. During downturns, by contrast, this relationship effectively disappears in both economic and statistical terms. Thus rising marginal costs during expansions appear to fuel inflation, whereas the emergence of economic slack during downturns by and large puts very little downward pressure on inflation. These findings alone may be one reason for the disparate views on the likely effect of fluctuations in economic activity on the cyclical behavior of inflation.

We then consider the extent to which the relationship between inflation and economic activity has evolved over time. We do this by estimating the sensitivity of both producer and consumer price inflation to economic slack using 15-year rolling-window regressions, starting in the early 1960s. We document that this relationship has indeed weakened substantially over the past 50 years or so—the response of inflation to economic slack has fallen by a factor of two over this time period. These findings are robust to using both headline inflation measures, as well as core measures of inflation that remove the direct influence of swings in food and energy prices. They are also robust to measuring economic slack using alternative concepts such as the output gap or the unemployment gap.

We next consider the responsiveness of inflation to economic activity at the industry level. In this analysis, we exploit the rich cross-sectional dimension of our data and can directly control for the common aggregate component driving both inflation and output. We again find that fluctuations in output are an important determinant of inflation—indeed, the estimated response of industry-level inflation to variation in industry-level output is very similar to that obtained from aggregate time-series data over comparable sample periods. One key difference between our aggregate time-series and industry-level findings is that inflation at the industry level is more responsive to movements in output during downturns than during expansions.

Using both the industry-level and aggregate time-series data, we then examine the extent to which an increase in trade exposure has altered the response of inflation to fluctuations in economic activity. Here again our findings are consistent across both aggregate and industry-level data. In the time-series, the rising exposure of the U.S. economy to international trade can indeed explain a significant fraction of the overall decline in responsiveness of aggregate inflation to economic slack. This result is buttressed by our cross-sectional evidence, which shows that increased trade exposure attenuates the response of inflation to fluctuations in output across industries.

The analysis discussed above, however, does not directly determine the causal impact of fluctuations in economic activity on inflation. While demand shocks typically move inflation and output in the same direction, supply shocks have the opposite effect. Thus any attenuation in the observed response of inflation to output may be due to changes in the mixture of demand and supply shocks that the U.S. economy has experienced over our sample period. To address this issue, we examine the effect of identified shocks to both aggregate demand and supply on industry-level outcomes. In this exercise, we are explicitly interested in the extent to which the intensity of trade exposure at the industry level alters the responsiveness of inflation to such aggregate shocks.

Given the high dimensionality of our industry-level data, we consider the dynamic effects of identified aggregate demand and supply shocks using a Factor-Augmented Vector Autoregression (FAVAR) model, whereby the information contained in the large panel of industries is summarized by a small subset of common factors. Using this framework, we study how shocks to broad financial conditions (i.e., aggregate demand shocks) and shocks to commodity prices (i.e., aggregate supply shocks) affect the dynamics of price and wage inflation, output, and employment at the industry level. We focus on these two aggregate disturbances because we view them as readily identified from economic and financial time-series data; moreover, these two sources of business cycle fluctuations account for a sizable fraction of the variability in output and inflation over the past 30 years.

Using the FAVAR approach, we first document that a tightening in broad financial conditions causes a significant decline in price and wage inflation, as well as in output and employment growth across all industries. Thus financial shocks deliver the positive comovement between inflation and output that is typically associated with shocks to aggregate demand. In contrast, commodity price shocks cause sharp increases in inflation and a significant reduction in economic activity, as measured by the growth of output. Again, these effects are widespread across industries.

Within the FAVAR framework, we then examine the extent to which responses of inflation and output to these two shocks differ across industries based on their trade exposure. Our results indicate that industries with a high trade exposure exhibit a substantially smaller response of inflation to movements in output induced by the unanticipated changes in broad financial conditions and to movements in output induced by shocks to commodity prices, relative to industries with a low trade exposure. This differential dynamics occur despite the fact that the effect of such shocks on economic activity is virtually identical across these two industrial groupings. Translated into the movement of inflation—relative to output—our results imply that in response to such shocks, inflation is three times more responsive to changes in output for industries with a low trade exposure, compared with industries with a high trade exposure. These findings further support the argument that trade exposure attenuates the link between inflation and economic activity and that increased trade exposure is indeed a likely source of the reduced responsiveness of aggregate inflation to economic slack.

The remainder of the paper is organized as follows follows. Section 2 considers the aggregate time-series relationship between inflation and economic activity and documents its evolution over time. Section 3 explores the relationship between inflation and economic activity using industry-level data and documents the extent to which differences in trade exposure across industries affect this relationship. Section 4 provides the FAVAR analysis, which shows how industry-level variables respond to both financial and commodity price shocks, as well as the extent to which these responses differ across industries depending on their exposure to international trade. And lastly, Section 5 concludes.

2 Aggregate Phillips Curve

In this section, we establish some stylized facts about the relationship between inflation and economic slack using aggregate time-series data. While the vast literature on this topic has focused largely on consumer price inflation, we analyze inflation dynamics at both the producer and consumer levels; the focus on the former is especially important because movements in producer prices directly capture the price response of production units to changes in the underlying economic conditions.[3] The solid line in Panel A of Figure 1 shows the behavior of prices received by U.S. producers for their output, measured by the four-quarter percent change in the Producer Price Index (PPI) for final demand, while the solid line in Panel B shows the four-quarter percent change in the Consumer Price Index (CPI), a measure of prices paid by urban consumers for a market basket of consumer goods and services; the dotted lines in each panel show the corresponding core inflation, which strips out from headline each price index items belonging to the food or energy categories.[4]

Clearly evident in the data are several distinct inflation regimes. First the 1970s, a period of high and volatile inflation that early on was influenced importantly by the OPEC-induced increases in oil prices (Hamilton, 1983, 2003) and later by the Federal Reserve's overly optimistic view of the natural rate of unemployment (Orphanides and Williams, 2013). The early 1980s, in contrast, were marked by a gradual step-down in inflation reflecting the tightening of monetary policy under Chairman Volcker, who was determined to fight inflation and reverse the rise in inflation expectations (Lindsey et al., 2005). Since the mid-1980s, inflation—at both the producer and consumer levels—has stabilized in the narrow range between two and 2.5 percent, a pattern consistent with the well-anchored inflation expectations engendered by credible monetary policy, aimed at achieving its so-called dual mandate.[5]

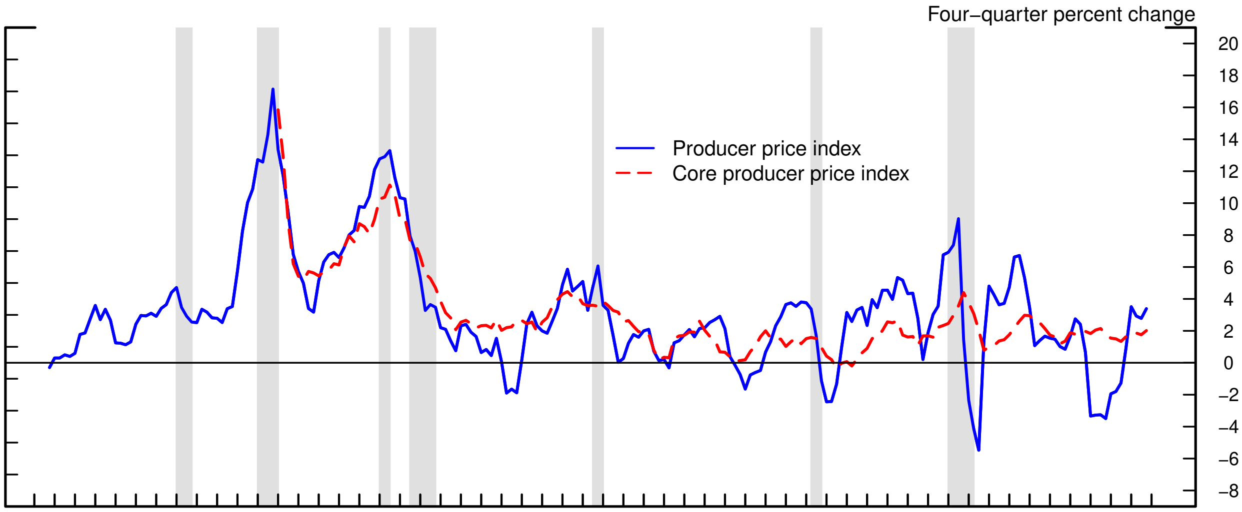
A striking way to illustrate how inflation is unresponsive to fluctuations in economic activity—in other words, how flat is the Phillips curve—is to focus on economic downturns. To that end, Figure 2 examines the relationship between inflation and economic activity during the the past five recessions, downturns in which supply-side disturbances—which cause inflation and economic

[3]It is worth noting that the frequency of price changes in the narrow-item categories that are both in the consumer and producer micro-level price data sets collected by the Bureau of Labor Statistics are highly correlated (see Nakamura and Steinsson, 2008).

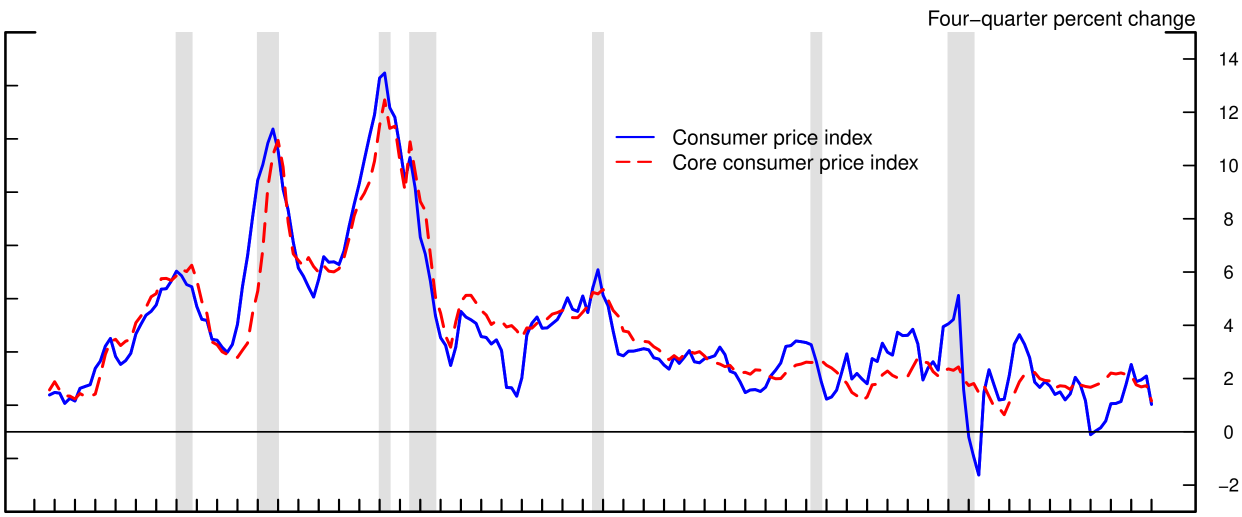
[4]Each quarterly price index is constructed as a simple average of the monthly (seasonally adjusted) index values, and four-quarter percent changes are computed as 100 times the four-quarter log-difference of the specified series. In addition, while we use the CPI to measure inflation at the consumer level, all the results reported below are robust to using the personal consumption expenditure (PCE) price index to track the change in prices of goods and services purchased by the U.S. consumers throughout the economy.

[5]The Full Employment and Balanced Growth Act of 1978—more commonly known as the Humprey-Hawkins Act—established price stability and full employment as national economic policy objectives.

Figure 1: Producer and Consumer Price Inflation



A. Producer price inflation



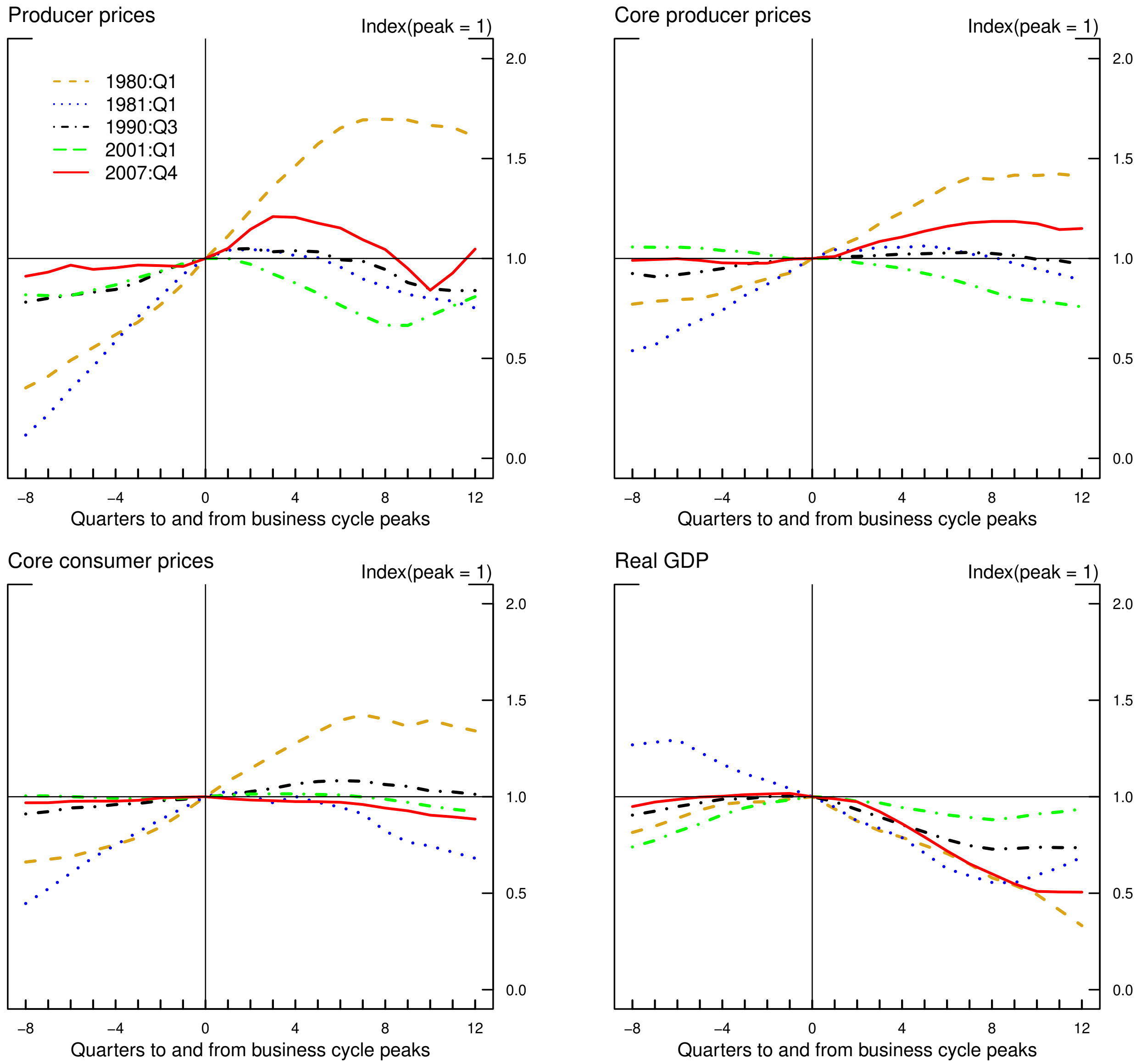
B. Consumer price inflation

Note: All price indexes are seasonally adjusted. The shaded vertical bars denote the NBER-dated recessions.
Source: Bureau of Labor Statistics.

activity to move in opposite directions—were arguably not the dominant factors. The first three panels of the figure depict the behavior of detrended prices two years before and three years after each NBER-dated cyclical peak since the early 1980s; the bottom right panel, by contrast, shows the corresponding dynamics of detrended real GDP, a simple measure of economic slack.

As shown in the top two panels, with the exception of the 2001 recession, producer prices showed virtually no deceleration during the past five economic downturns, relative to their trends. And even during the bursting of the tech bubble in 2001, the decline in both the headline and core PPI

FIGURE 2: Inflation and Output in Recessions



NOTE: The panels depict the behavior of various price measures and real GDP eight quarters before and 12 quarters after the specified NBER-dated cyclical peak. All series are plotted as deviations from their respective stochastic trends, estimated using the Hamilton (2017) filter.
SOURCE: Authors' calculations using data from the Bureau of Economic Analysis; Bureau of Labor Statistics; and Federal Reserve Board.

is due entirely to the plunge in producer prices in the immediate aftermath of the September 11 terrorist attacks—in October 2001, the Bureau of Labor Statistics reported that the PPI dropped almost 20 percent at an annual rate.[6] As shown in the bottom left panel, the resilience of inflation in response to the emergence of substantial economic slack is also evident at the consumer level.

[6]It is also worth noting that the sharp increase in commodity prices prompted by the First Gulf War confounds the behavior of PPI inflation during the 1990 recession to some extent.

At the same time, as shown in the bottom right panel, real GDP declined markedly—relative to its trend—during these five episodes.

2.1 Baseline Estimates

To investigate more formally how the relationship between inflation and fluctuations in economic activity may have changed over time, we begin by estimating a standard Phillips curve specification, which expresses inflation as a linear function of expected inflation and a measure of economic slack. Specifically, letting lower-case variables denote variables in logarithms and defining $\Delta_h x_{t+h} = \frac{400}{h}(x_{t+h} - x_t)$, we estimate the following Phillips curve specification:

$$\Delta_{h+1} p_{t+h} = \mu + \lambda \mathrm{gap}_t + \sum_{s=1}^{4} \phi_s \Delta p_{t-s} + \epsilon_{t+h}, \tag{1}$$

where p_t denotes the logarithm of a price index (i.e., PPI or CPI) and gap_t is a measure of economic slack, a degree of resource over- or under-utilization. Thus equation (1) posits a relationship between (annualized) inflation from quarter $t-1$ to quarter $t+h$ and a measure of economic slack in quarter t, while the lags of inflation Δp_{t-s}, $s = 1, \dots, 4$, are a proxy for expected inflation (see Gordon, 1982; Stock and Watson, 2009).[7] In this canonical formulation, the error term ϵ_{t+h} encompasses cost-push shocks—shock to commodity prices, for example—which are assumed to be uncorrelated with the contemporaneous economic slack.

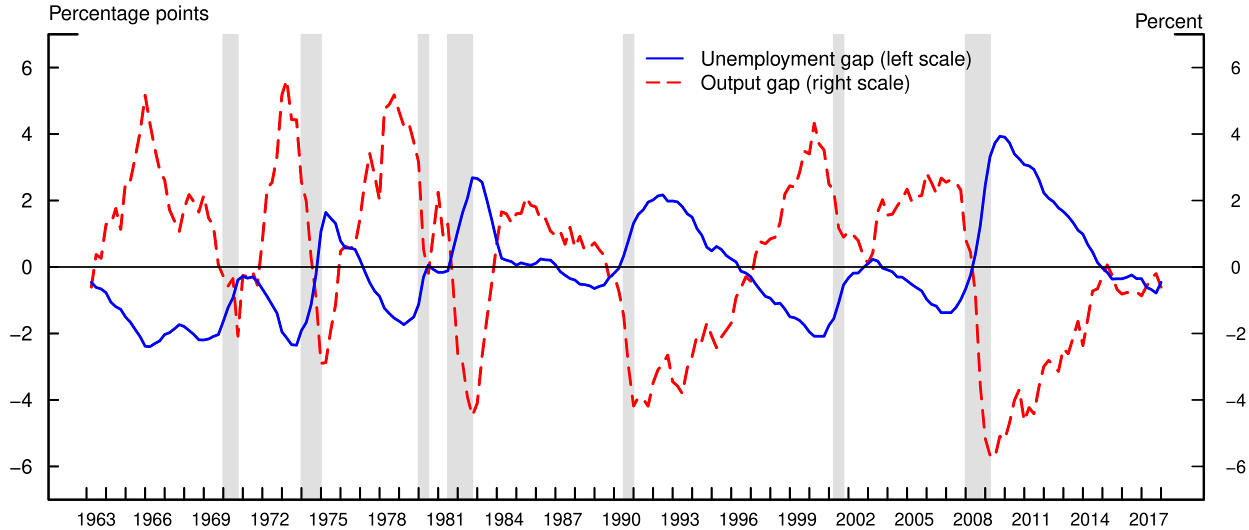
Figure 3 shows two measures of economic slack used in our analysis: the output gap and the unemployment gap. The output gap, denoted by $[y_t - y_t^*]$ is defined as (100 times) the logarithm of the ratio of real GDP to its estimate of potential, while the unemployment gap, denoted by $[U_t - U_t^*]$, corresponds to the unemployment rate less its estimate of the natural rate. The estimates of both potential real GDP and the natural rate of unemployment are taken from the FRB/US model, a large-scale estimated general equilibrium model of the U.S. economy that has been in use at the Federal Reserve Board since 1996. While the definition of these two slack measures naturally produces series of the opposite sign, they paint a very similar picture of cyclical resource utilization over the last 50 years or so. One exception to this pattern has occurred during the past several years, a period in which the unemployment rate has moved below its natural rate, whereas the real GDP has yet to return to its potential.[8]

Table 1 present estimates of the coefficient λ for producer price inflation at horizons of one and four quarters (i.e., $h = 1, 4$), with Panel A showing estimates of λ for headline PPI inflation and Panel B showing estimates of λ for core PPI inflation; the corresponding estimates of λ for consumer price inflation—both headline and core—are shown in Table 2.

[7] An alternative approach to using lagged values of inflation to capture expected inflation would be to use survey measures of expected inflation. However, as documented by Mankiw et al. (2004), such survey measures do not appear to be consistent with either rational expectations or adaptive expectations used in specification (1).

[8] Movements in the output gap can be interpreted as capturing fluctuations in real marginal cost, which micro-founded models emphasize as a key determinant of inflation dynamics (see Roberts, 1995; Galí and Gertler, 2000; Galí et al., 2001; Sbordone, 2002; Galí et al., 2007).

FIGURE 3: Economic Slack



NOTE: The output gap is defined as (100 times) the log-ratio of real GDP to its estimate of potential; the unemployment gap is defined as the civilian unemployment rate less its estimate of the natural rate. The shaded vertical bars denote the NBER-dated recessions.
SOURCE: Bureau of Economic Analysis; Bureau of Labor Statistics; and Federal Reserve Board.

According to the entries in Panel A of Table 1, fluctuations in economic slack have a significant effect on the subsequent behavior of producer prices. A decrease in resource utilization of one percentage point in quarter t—that is, a decline in the output gap or a rise in the unemployment gap of that magnitude—is estimated to reduce annualized headline producer price inflation over the next several quarters about 40 basis points. The corresponding estimates for core PPI inflation shown in Panel B are about one-half as large as those reported in Panel A, though the estimates are significant in both economic and statistical terms. As shown in Table 2, economic slack is also a significant determinant of consumer price inflation. In that case, a decrease in resource utilization of one percentage point is estimated to shave off about 25 basis points from annualized CPI inflation over the subsequent few quarters.

As a first pass on the question of whether the relationship between economic slack and subsequent inflation may have changed over the past 50 years or so, we report results of two tests. The first is the well-known Andrews (1993) test of a structural break—at an unknown date—in the coefficient λ. The second is the Elliott and Müller (2006) test of stability of the coefficient λ, which encompasses diverse forms of parameter instability—from relatively rare (including a single break) to frequent small breaks; persistent temporal parameter variation; and breaks occurring with a regular pattern.[9] This statistical analysis, however, yields a mixed picture. Turning first to producer prices (Table 1), the Andrews (1993) test provides strong evidence of a structural break

[9] In both tests, the null hypothesis is that the coefficient λ is stable over the sample period. The alternative in the Andrews (1993) test is that $\lambda = \lambda_1$ for $t = 1, 2, \ldots, \tau - 1$ and $\lambda = \lambda_2$ for $t = \tau, \tau + 1, \ldots T$, where τ is the unknown (single) break date. The alternative in the Elliott and Müller (2006) test is $\lambda = \lambda_t$, where the time variation in the parameter λ_t is unspecified and can take on a variety of forms.

Table 1: Phillips Curve – Producer Price Inflation

Explanatory Variables	$h=1$ (1)	$h=1$ (2)	$h=4$ (3)	$h=4$ (4)
A. Producer Prices				
$[y_t - y_t^*]$	0.356**	.	0.414***	.
	(0.144)		(0.153)	
$[U_t - U_t^*]$	.	−0.396*	.	−0.469*
		(0.238)		(0.257)
Sum: inflation lags[a]	0.578***	0.600***	0.470***	0.495***
	(0.113)	(0.113)	(0.093)	(0.100)
sup W[b]	15.185***	11.345**	33.370***	23.284***
	[81:Q2]	[91:Q4]	[80:Q3]	[93:Q4]
q_{LL}[c]	−6.230	−5.375	−5.297	−4.325
Adj. R^2	0.360	0.333	0.392	0.343
B. Core Producer Prices				
$[y_t - y_t^*]$	0.186***	.	0.223***	.
	(0.056)		(0.067)	
$[U_t - U_t^*]$	.	−0.243**	.	−0.273**
		(0.105)		(0.131)
Sum: inflation lags[a]	0.776***	0.797***	0.730***	0.755***
	(0.071)	(0.076)	(0.071)	(0.081)
sup W[b]	21.278***	18.000***	70.033***	39.261***
	[81:Q4]	[93:Q4]	[81:Q4]	[82:Q3]
q_{LL}[c]	−9.554**	−7.550*	−6.304	−5.737
Adj. R^2	0.743	0.725	0.760	0.727

Note: Sample: 1962:Q2 to 2017:Q4 for the headline PPI (Panel A); and 1974:Q1 to 2017:Q4 for the core PPI (Panel B). The dependent variable in each Phillips curve specification is $\Delta_{h+1} p_{t+h}$, the annualized log-difference in the specified price index from date $t-1$ to date $t+h$. Explanatory variables: $[y_t - y_t^*]$ = output gap; and $[U_t - U_t^*]$ = unemployment gap. All specifications include a constant and lags $1, \ldots, 4$ of Δp_t (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the "lag-length" parameter equal to four: * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Sum of coefficients on Δp_{t-s}, $s = 1, \ldots, 4$.

[b] The Andrews (1993) sup-Wald statistic of the null hypothesis that there is no structural break in the coefficient on economic slack; the estimated break dates are reported in brackets below.

[c] The Elliott and Müller (2006) q_{LL} statistic of the null hypothesis that the coefficient on economic slack is constant over time.

in λ, with the point estimate of a break date generally falling in the early 1980s, a result consistent with that of Roberts (2006). The evidence of parameter instability from the Elliott and Müller (2006) test, in contrast, is considerably weaker. A similar picture emerges when we look at consumer prices (Table 2). Here again, the Andrews (1993) test strongly suggest a structural break in λ that occurred in the early 1980s, whereas the results from the Elliott and Müller (2006) test are far less conclusive.

All told, the results reported in Tables 1 and 2 clearly indicate an important role—in both

Table 2: Phillips Curve – Consumer Price Inflation

	$h=1$		$h=4$	
Explanatory Variables	(1)	(2)	(3)	(4)
A. Consumer Prices				
$[y_t - y_t^*]$	0.258***	.	0.318***	.
	(0.075)		(0.084)	
$[U_t - U_t^*]$	.	−0.321***	.	−0.380***
		(0.120)		(0.128)
Sum: inflation lags[a]	0.779***	0.795***	0.690***	0.709***
	(0.066)	(0.070)	(0.068)	(0.077)
$\sup W$[b]	34.118***	28.008***	70.231***	44.548***
	[83:Q1]	[83:Q2]	[83:Q1]	[83:Q1]
q_{LL}[c]	−8.199*	−6.892	−6.347	−4.986
Adj. R^2	0.657	0.635	0.676	0.632
B. Core Consumers Prices				
$[y_t - y_t^*]$	0.176***	.	0.265***	.
	(0.044)		(0.060)	
$[U_t - U_t^*]$	.	−0.263***	.	−0.364***
		(0.079)		(0.107)
Sum: inflation lags[a]	0.868***	0.875***	0.787***	0.797***
	(0.056)	(0.060)	(0.065)	(0.074)
$\sup W$[b]	38.828***	38.420***	112.255***	66.416***
	[83:Q1]	[83:Q1]	[83:Q1]	[83:Q1]
q_{LL}[c]	−8.639**	−6.259	−7.278*	−6.056
Adj. R^2	0.802	0.794	0.778	0.750

Note: Sample: 1962:Q2 to 2017:Q4. The dependent variable in each Phillips curve specification is $\Delta_{h+1}p_{t+h}$, the annualized log-difference in the specified price index from date $t-1$ to date $t+h$. Explanatory variables: $[y_t - y_t^*]$ = output gap; and $[U_t - U_t^*]$ = unemployment gap. All specifications include a constant and lags $1, \ldots, 4$ of Δp_t (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the "lag-length" parameter equal to four: * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] Sum of coefficients on Δp_{t-s}, $s = 1, \ldots, 4$.
[b] The Andrews (1993) sup-Wald statistic of the null hypothesis that there is no structural break in the coefficient on economic slack; the estimated break dates are reported in brackets below.
[c] The Elliott and Müller (2006) q_{LL} statistic of the null hypothesis that the coefficient on economic slack is constant over time.

economic and statistical terms—for economic slack as a determinant of cyclical inflation dynamics. Nevertheless, empirical Phillips curves of the type given by equation (1) predicted a significantly greater downward pressure on inflation—if not outright deflation—during the Great Recession than was actually realized. Economists have advanced a number of hypotheses to explain this case of "missing deflation." A prominent hypothesis that received a lot of attention in policy circles argues that the Federal Reserve's credibility has led businesses and households to discount inflation outcomes that fall outside the narrow range bracketing the Federal Open Market Committee's inflation target of two percent; this anchoring of agents' expectations has—through the standard expectational effects—prevented actual inflation from falling significantly below that level (see Bernanke, 2010; Yellen, 2013).

Another widely-cited hypothesis posits that the relevant measure of economic slack in empirical Phillips curves is not the overall unemployment rate gap, but rather the short-term unemployment rate.[10] Compared with the former, this latter indicator of slack increased notably less during the Great Recession and has also returned more quickly to its pre-recession levels, thus providing substantially less deflationary impetus. And although it has proven difficult to identify structural changes in the economy that could account for the diminished sensitivity of inflation to the level of unemployment, a number of economists have singled out the apparent flattening of the Phillips curve as an important reason for the fact that the U.S. economy did not experience a Fisherian debt-deflation spiral during the 2008–2009 global financial crisis (see Ball and Mazumder, 2011; Simon et al., 2013).[11]

In light of the results reported in Tables 1 and 2, it seems clear that a further investigation in the time-varying nature of the relationship between inflation and economic slack is warranted. However, before analyzing this question further, we document another important empirical feature of the canonical Phillips curve relationship that could potentially account for the disparate views on how fluctuations in economic activity affect inflation dynamics. In particular, we examine whether the relationship between inflation and economic slack is, as suggested by equation (1), symmetric. To do so, we estimate the following variant of the traditional Phillips curve:

$$\Delta_{h+1} p_{t+h} = \mu + \lambda_1 \text{gap}_t^{(+)} + \lambda_2 \text{gap}_t^{(-)} + \sum_{s=1}^{4} \phi_s \Delta p_{t-s} + \epsilon_{t+h}, \tag{2}$$

where $\text{gap}_t^{(+)}$ denotes either a positive output or a positive unemployment gap and vice-versa for $\text{gap}_t^{(-)}$. In other words, the asymmetric Phillips curve specification (2) allows the sensitivity of inflation to economic slack to differ between periods of resource over- and under-utilization.

To conserve space, we focus on the forecast horizon $h = 4$ when estimating specification (2), though the results for the one-quarter horizon were virtually the same. Table 3 reports the results for PPI inflation, while those pertaining to CPI inflation are reported in Table 4. Turning first to producer prices, the entries in Table 3 strongly indicate that the response of inflation to economic slack is different in periods when the economy is operating above its potential (or the unemployment rate is below its natural rate) from periods in which the economy is experiencing resource under-utilization. For example, according to column (1), the coefficient on the positive output gap is 1.088—and statistically highly significant—compared with the coefficient of −0.184 on the

[10] Underlying this argument is the idea that workers who have been unemployed for a relatively short time are the relevant margin for wage adjustment. The longer-term unemployed, by contrast, do not put much downward pressure on wages because these potential workers are disconnected from the labor market (see Stock and Watson, 2010b; Gordon, 2013; Krueger et al., 2014).

[11] Gilchrist and Zakrajšek (2016); Gilchrist et al. (2017), in contrast, emphasize how the interaction of financial distress and customer markets attenuated deflationary pressures during the Great Recession.

Table 3: Asymmetric Phillips Curve – Producer Price Inflation

	Producer Prices		Core Producer Prices	
Explanatory Variables	(1)	(2)	(3)	(4)
$[y_t - y_t^*]^{(+)}$	1.088***	.	0.422***	.
	(0.324)		(0.160)	
$[y_t - y_t^*]^{(-)}$	−0.184	.	0.079	.
	(0.219)		(0.095)	
$[U_t - U_t^*]^{(+)}$	.	0.215	.	−0.158
		(0.344)		(0.156)
$[U_t - U_t^*]^{(-)}$	.	−1.424**	.	−0.533
		(0.601)		(0.389)
$\Pr > W$[a]	0.009	0.050	0.122	0.427
Sum: inflation lags[b]	0.434***	0.487***	0.715***	0.752***
	(0.089)	(0.092)	(0.064)	(0.077)
Adj. R^2	0.456	0.382	0.768	0.730

Note: Sample: 1962:Q2 to 2017:Q4 for the headline PPI (columns 1–2); and 1974:Q1 to 2017:Q4 for the core PPI (columns 3–4). The dependent variable in each Phillips curve specification is $\Delta_5 p_{t+4}$, the annualized log-difference in the specified producer price index from date $t-1$ to date $t+5$. Explanatory variables: $[y_t - y_t^*]^{(+)}$ = positive output gap; $[y_t - y_t^*]^{(-)}$ = negative output gap; $[U_t - U_t^*]^{(+)}$ = positive unemployment gap; and $[U_t - U_t^*]^{(-)}$ = negative unemployment gap. All specifications include a constant and lags $1, \ldots, 4$ of Δp_t (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the "lag-length" parameter equal to four: * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] p-value for the test of equality of coefficients on positive and negative economic slack.

[b] Sum of coefficients on Δp_{t-s}, $s = 1, \ldots, 4$.

negative output gap, which is statistically indistinguishable from zero at conventional significance levels; in fact, a formal test rejects the null hypothesis that the two coefficients are equal at a one percent significance level. As shown in column (2), the same conclusion emerges when economic slack is measured by the unemployment gap. For core producer prices, columns (3) and (4), the differences in the coefficients on positive and negative slack are statistically less precise, though quite meaningful in economic terms.

As shown in Table 4, this form of asymmetry is even more evident in consumer prices. Regardless of whether economic slack is measured in product markets or the labor market, our estimates indicate that CPI inflation is highly sensitive to the degree of resource over-utilization in the economy, whereas resource under-utilization has no discernible effect on the behavior of inflation. Moreover, this result is robust to using both the headline and core measures of CPI inflation—in all instances, we strongly reject the null hypothesis that the coefficients on positive and negative economic slack are equal. The combination of results in Tables 3 and 4 would seem to indicate that rising marginal costs during expansions fuel inflation, whereas the emergence of economic slack during downturns puts essentially no downward pressure on inflation. It is not clear, however, what structural features of the economy could account for this striking asymmetry. But from a purely empirical perspective, these results help explain the resilience of prices—at both the producer and

TABLE 4: Asymmetric Phillips Curve – Consumer Price Inflation

	Consumer Prices		Core Consumer Prices	
Explanatory Variables	(1)	(2)	(3)	(4)
$[y_t - y_t^*]^{(+)}$	0.736***	.	0.533***	.
	(0.183)		(0.117)	
$[y_t - y_t^*]^{(-)}$	−0.057	.	0.018	.
	(0.101)		(0.070)	
$[U_t - U_t^*]^{(+)}$	.	0.089	.	0.028
		(0.153)		(0.119)
$[U_t - U_t^*]^{(-)}$	.	−1.037***	.	−0.911***
		(0.320)		(0.245)
$\Pr > W$[a]	0.002	0.008	0.002	0.003
Sum: inflation lags[b]	0.689***	0.726***	0.798***	0.824***
	(0.057)	(0.072)	(0.060)	(0.072)
Adj. R^2	0.720	0.664	0.800	0.777

NOTE: Sample: 1962:Q2 to 2017:Q4. The dependent variable in each Phillips curve specification is $\Delta_5 p_{t+4}$, the annualized log-difference in the specified consumer price index from date $t-1$ to date $t+4$. Explanatory variables: $[y_t - y_t^*]^{(+)}$ = positive output gap; $[y_t - y_t^*]^{(-)}$ = negative output gap; $[U_t - U_t^*]^{(+)}$ = positive unemployment gap; and $[U_t - U_t^*]^{(-)}$ = negative unemployment gap. All specifications include a constant and lags $1, \ldots, 4$ of Δp_t (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the "lag-length" parameter equal to four: * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] p-value for the test of equality of coefficients on positive and negative economic slack.
[b] Sum of coefficients on Δp_{t-s}, $s = 1, \ldots, 4$.

consumer levels—to the emergence of substantial and prolonged economic slack.

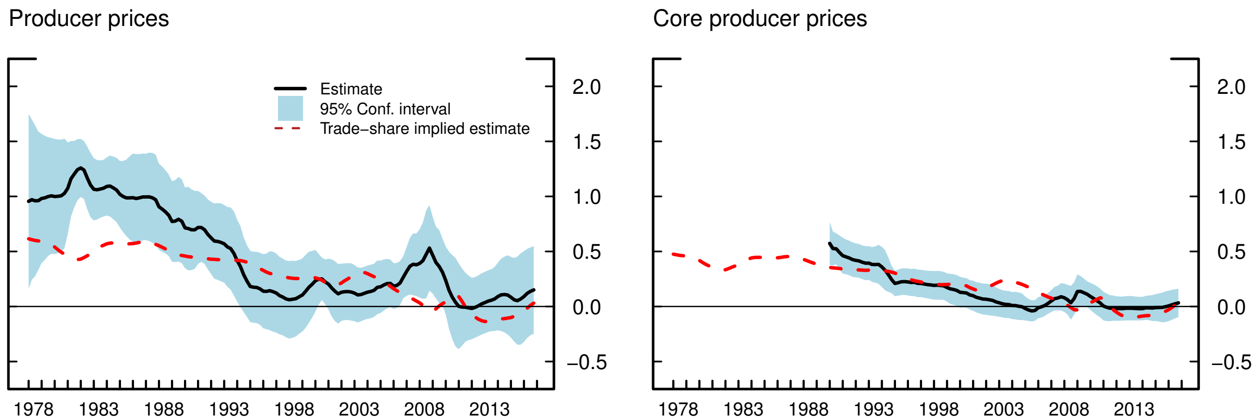
2.2 Time-Varying Estimates

We now return to the question of whether and how has the relationship between inflation and economic slack changed over time. As a simple and relatively straightforward way to consider the possibility of time variation in the coefficient λ—as well as in other parameters of the standard Phillips curve—we re-estimate specification (1) using 15-year rolling windows. We then plot the time-varying coefficient on the specified measure of economic slack, along with its 95-percent confidence interval. Again, to conserve space, we focus on the Phillips curve specifications for inflation at the horizon of four quarters (i.e., $h = 4$). The resulting time-varying estimates of the coefficient λ, for both the headline and core PPI inflation, are shown in Figure 4, with Panel A showing the time-varying sensitivity to the output gap and Panel B showing the time-varying sensitivity to the unemployment gap; the comparable estimates for CPI inflation are shown in Figure 5.[12]

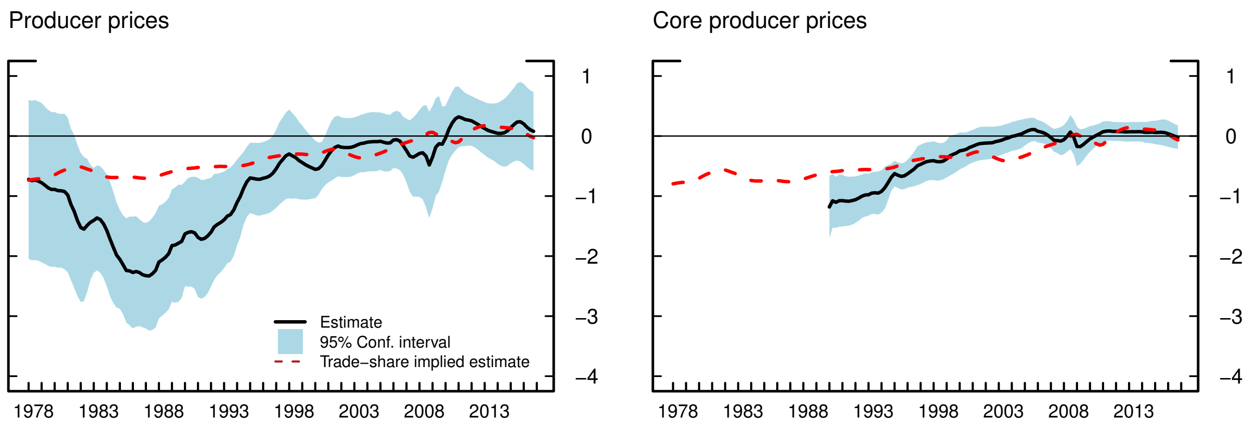
The left chart in Panel A of Figure 4 shows the evolution of the response of headline PPI

[12] The convention is that the data point labeled "1995:Q4" represents an estimate based on the 1980:Q1–1995:Q4 sample period. For both the headline producer and consumer price inflation, as well as for the core consumer price inflation, our sample period—allowing for lags—starts in 1962:Q2, so that the rolling-window estimates begin in 1978:Q1 and run through 2017:Q4, the end of our sample period. Core producer prices, by contrast, start in 1974:Q1, which implies that the first rolling-window estimates become available in 1990:Q1.

Figure 4: Time-Varying Coefficient on Economic Slack
(Phillips Curve – Producer Price Inflation)



A. Economic slack: output gap



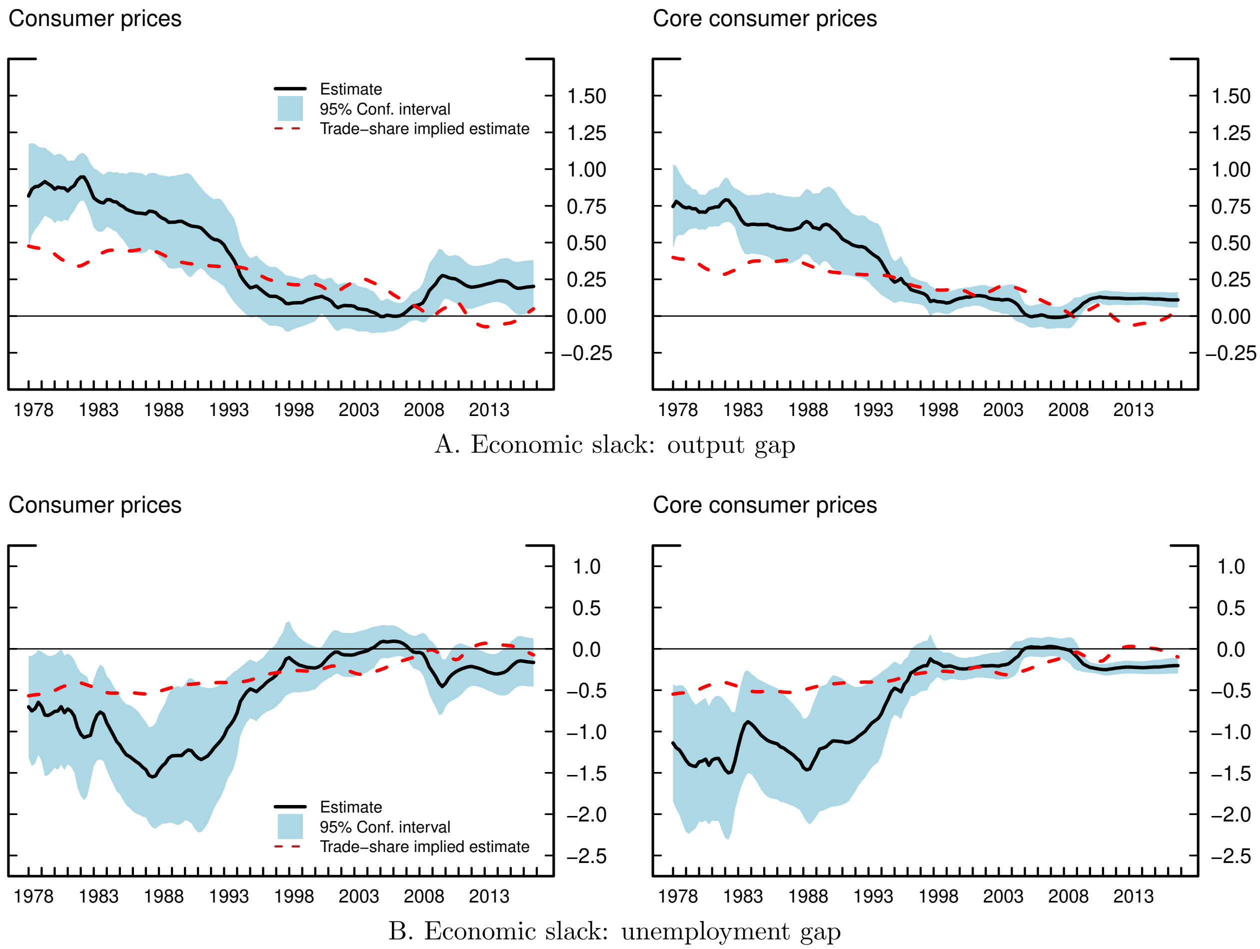
B. Economic slack: unemployment gap

Note: The dependent variable in each Phillips curve specification is $\Delta_5 p_{t+4}$, the annualized log-difference in the specified producer price index from date $t-1$ to date $t+4$. The solid line in each panel depicts the time-varying coefficient on the specified measure of economic slack estimated using a 60-quarter moving window; the dashed lines depict the corresponding time-varying coefficients implied by specifications (3) and (4) in Table 5 (see notes to the table and the main text for details).

inflation to the output gap. In the early part of the sample, the estimates of λ are greater than one and significantly different from zero, according to the 95-percent confidence intervals. Starting in the mid-1980s, however, these estimated sensitivities begin to decline steadily before stabilizing in the late 1990s. From then onward, the estimates of λ fluctuate in a fairly narrow of range between zero and 0.5, though for most of this latter sample period, one would not reject the hypothesis that the coefficient on the output gap is statistically different from zero.

The left chart in Panel B shows the evolution of the response of headline PPI inflation to the unemployment gap. We observe roughly the same general pattern in this case. The estimates of λ start out negative—and large in economic terms—as well statistically different from zero, according

FIGURE 5: Time-Varying Coefficient on Economic Slack
(Phillips Curve – Consumer Price Inflation)

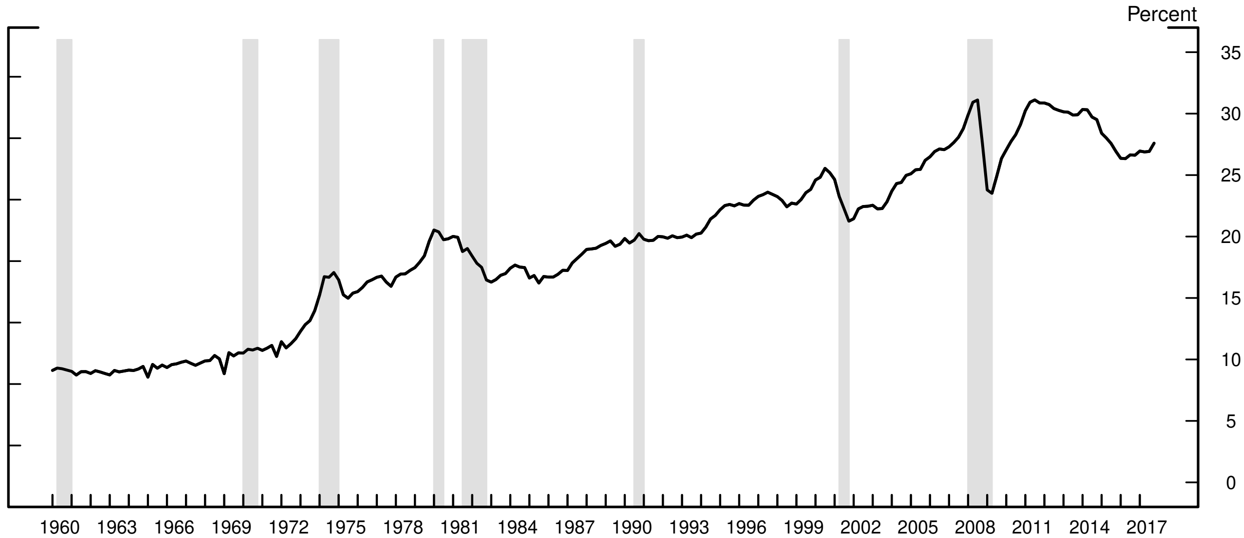


NOTE: The dependent variable in each Phillips curve specification is $\Delta_5 p_{t+4}$, the annualized log-difference in the specified consumer price index from date $t-1$ to date $t+4$. The solid line in each panel depicts the time-varying coefficients on the specified measure of economic slack estimated using a 60-quarter moving window; the dashed lines depict the corresponding time-varying coefficients implied by specifications (3) and (4) in Table 6 (see notes to the table and the main text for details).

to the conventional significance levels. Once the late 1980s enter the sample period, however, the estimates begin to converge rapidly to zero. The estimated response of headline PPI inflation to the unemployment gap then remains around zero for the remainder of the sample period.

The corresponding right charts of Figure 4 trace out the estimated sensitivities of core PPI inflation to the output gap (Panel A) and the unemployment gap (Panel B). Although the sample begins later in this instance, the rolling-window estimates of the coefficient λ in the Phillips curve for core PPI inflation are much more precisely estimated, compared with their counterparts for headline inflation. The estimates of λ for the output gap begin at about 0.5 for the sample that extends from the mid-1970s to the end of the 1980s and then decline monotonically to zero as the

Figure 6: U.S. Trade Share



Note: The trade share is defined as the sum of the nominal value of U.S. imports and exports, expressed as a percent of nominal GDP. The shaded vertical bars denote the NBER-dated recessions.
Source: Bureau of Economic Analysis.

sample period moves forward; in fact, the estimate of λ based on the last 15 years of available data implies a sensitivity of core PPI inflation to the output gap that is economically and statistically indistinguishable from zero. The time-series pattern of coefficients on the unemployment gap is very similar: The estimates of λ start out negative, large in absolute value, and are precisely estimated and then converge to zero by the end of the 1990s.

Figure 5 shows the time-varying coefficient estimates on economic slack for both the headline and core measures of CPI inflation. As before, Panel A shows coefficient estimates on the output gap, while the corresponding estimates for the unemployment gap are shown in Panel B. Consistent with the full-sample estimates of λ reported in Panel A of Table 2, the time-varying coefficient estimates of the response of inflation to the output gap for headline CPI inflation are very similar to those for core inflation, both in terms of their magnitude and their evolution over time. They also show a pattern similar to that shown in Figure 4: The estimates of λ are positive, economically and statistically significant in the early part of the sample, and then begin to decline sharply once the 1990s enter the estimation window. In contrast to the estimated response coefficients for PPI inflation shown in Panel A of Figure 4, the sensitivity of CPI inflation to the output gap is estimated to have increased notably at the end of our sample period. That said, these late-sample estimates of λ, though statistically different from zero, are only about one-fourth of those estimated during the early part of our sample period. According to Panel B of Figure 5, these patterns are robust to using the unemployment gap, rather than the output gap, as a measure of economic slack.

While there are a variety of phenomena that may help explain the declining sensitivity of aggregate inflation to fluctuations in economic activity, we are specifically interested in the extent

TABLE 5: Phillips Curve and the Trade Share – Producer Price Inflation

	$h=1$		$h=4$	
Explanatory Variables	(1)	(2)	(3)	(4)
A. Producer Prices				
$[y_t - y_t^*]$	0.968**	.	1.459**	.
	(0.449)		(0.584)	
$[y_t - y_t^*] \times \text{TrdShr}_{t-1}$	−0.030	.	−0.052*	.
	(0.023)		(0.027)	
$[U_t - U_t^*]$	.	−1.349**	.	−1.759**
		(0.674)		(0.822)
$[U_t - U_t^*] \times \text{TrdShr}_{t-1}$	.	0.047	.	0.063*
		(0.033)		(0.038)
Sum: inflation lags[a]	0.583***	0.604***	0.479***	0.500***
	(0.111)	(0.108)	(0.086)	(0.093)
Adj. R^2	0.369	0.342	0.440	0.371
B. Core Producer Prices				
$[y_t - y_t^*]$	0.903***	.	1.125***	.
	(0.309)		(0.305)	
$[y_t - y_t^*] \times \text{TrdShr}_{t-1}$	−0.031**	.	−0.040***	.
	(0.014)		(0.014)	
$[U_t - U_t^*]$	.	−1.591***	.	−1.851***
		(0.596)		(0.648)
$[U_t - U_t^*] \times \text{TrdShr}_{t-1}$	.	0.056**	.	0.065**
		(0.024)		(0.026)
Sum: inflation lags[a]	0.751***	0.790***	0.698***	0.747***
	(0.067)	(0.067)	(0.058)	(0.068)
Adj. R^2	0.762	0.742	0.794	0.754

NOTE: Sample: 1962:Q2 to 2017:Q4 for the headline PPI (Panel A); and 1974:Q1 to 2017:Q4 for the core PPI (Panel B). The dependent variable in each Phillips curve specification is $\Delta_{h+1}p_{t+h}$, the annualized log-difference in the specified price index from date $t-1$ to date $t+h$. Explanatory variables: $[y_t - y_t^*]$ = output gap; $[U_t - U_t^*]$ = unemployment gap; and TrdShr_{t-1} = eight-quarter moving-average of the trade share. All specifications include a constant and lags $1, \ldots, 4$ of Δp_t (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the "lag-length" parameter equal to four: * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] Sum of coefficients on Δp_{t-s}, $s = 1, \ldots, 4$.

to which increased globalization and trade may have contributed to the flattening of the Phillips curve. The notion that increased trade may help account for such changes is consistent with the rising trade intensity in the United States—defined as the sum of exports and imports relative to GDP—shown in Figure 6. According to this metric, the trade intensity of the U.S. economy has risen by nearly a factor of three over the past 50 years or so.

To test the hypothesis that increased trade intensity of the U.S. economy may have contributed to the observed decline of the sensitivity of inflation to economic slack, we estimate the following variant of our baseline Phillips curve specification:

$$\Delta_{h+1}p_{t+h} = \mu + \lambda_1 \text{gap}_t + \lambda_2\big[\text{gap}_t \times \text{TrdShr}_{t-1}\big] + \sum_{s=1}^{4}\phi_s\Delta p_{t-s} + \epsilon_{t+h}, \tag{3}$$

where TrdShr_t denotes an eight-quarter moving average of the U.S. trade share shown in Figure 6. The resulting coefficient estimates of λ_1 and λ_2 for PPI inflation are reported in Table 5, while those for CPI inflation are reported in Table 5.

According to the entries reported in Panel A of Table 5, the coefficient on the interaction term between the output gap and the trailing moving average of the U.S trade share is negative—though not statistically different from zero—at the one-quarter horizon (column 1) and negative and marginally significant at the four-quarter horizon (column 3). Similarly, the interaction effect between the unemployment gap and trade share is positive and imprecisely estimated for $h = 1$, whereas the coefficient on the interaction term for $h = 4$ is positive and statistically different from zero at the 10-percent significance level. On balance, therefore, the evidence based on headline PPI inflation does not seem to support strongly the hypothesis that increased trade exposure of the U.S. economy can explain the decline in the sensitivity of inflation to fluctuations in economic activity.

As shown in Panel B, however, the corresponding estimates for core PPI inflation paint a very different picture. The coefficients on the interaction terms between the output gap and trade share are negative and quite precisely estimated at both the one- and four-quarter horizons (columns 1 and 3). And similarly, the coefficients on the interaction terms between the unemployment gap and trade share are negative and statistically different from zero for both $h = 1$ and $h = 4$ (columns 2 and 4). Moreover, these estimates are economically meaningful. At the four-quarter horizon, they imply that when the trade share was at the 5th percentile of its distribution, the sensitivity of core PPI inflation to the output gap was 0.766 (std. error = 0.186) and -1.262 (std. error = 0.416) when the unemployment gap is used to gauge the degree of resource utilization in the economy; the corresponding estimates at the 95th percentile, in contrast, are -0.058 (std. error = 0.122) and 0.092 (std. error = 0.188), respectively. In other words, these results indicate a robust relationship between the rising trade share and the diminished sensitivity of core PPI inflation to fluctuations in economic activity.

In Table 6, we report the estimates of coefficients λ_1 and λ_2 for Phillips curve specifications involving headline (Panel A) and core (Panel B) CPI inflation. These results again imply an economically large and statistically significant reduction in the responsiveness of inflation to economic slack as the trade share rises. This is true for both the headline and core measures of CPI inflation and holds at both the one- and four-quarter horizons. Moreover, the strong attenuation of the response of CPI inflation to economic slack is robust to using either the output or the unemployment gap as a gauge of cyclical resource utilization.

To summarize how the increasing exposure of the U.S. economy to international trade over the past 50 years affected the responsiveness of inflation to fluctuations in economic activity, we

Table 6: Phillips Curve and the Trade Share – Consumer Price Inflation

	$h=1$		$h=4$	
Explanatory Variables	(1)	(2)	(3)	(4)
A. Consumer Prices				
$[y_t - y_t^*]$	0.728***	.	1.093***	.
	(0.231)		(0.311)	
$[y_t - y_t^*] \times \text{TrdShr}_{t-1}$	−0.023**	.	−0.038***	.
	(0.011)		(0.013)	
$[U_t - U_t^*]$	.	−0.997***	.	−1.282***
		(0.353)		(0.425)
$[U_t - U_t^*] \times \text{TrdShr}_{t-1}$	.	0.033**	.	0.044**
		(0.016)		(0.018)
Sum: inflation lags[a]	0.801***	0.812***	0.727***	0.734***
	(0.063)	(0.067)	(0.063)	(0.075)
Adj. R^2	0.670	0.645	0.721	0.656
B. Core Consumers Prices				
$[y_t - y_t^*]$	0.526***	.	0.918∗∗∗	.
	(0.133)		(0.200)	
$[y_t - y_t^*] \times \text{TrdShr}_{t-1}$	−0.017***	.	−0.032***	.
	(0.005)		(0.008)	
$[U_t - U_t^*]$	.	−0.802***	.	−1.197***
		(0.237)		(0.340)
$[U_t - U_t^*] \times \text{TrdShr}_{t-1}$	.	0.026***	.	0.040***
		(0.009)		(0.013)
Sum: inflation lags[a]	0.891***	0.896***	0.831***	0.851***
	(0.053)	(0.058)	(0.061)	(0.072)
Adj. R^2	0.811	0.803	0.815	0.774

Note: Sample: 1962:Q2 to 2017:Q4. The dependent variable in each Phillips curve specification is $\Delta_{h+1}p_{t+h}$, the annualized log-difference in the specified price index from date $t-1$ to date $t+h$. Explanatory variables: $[y_t - y_t^*]$ = output gap; $[U_t - U_t^*]$ = unemployment gap; and TrdShr_{t-1} = eight-quarter moving-average of the trade share. All specifications include a constant and lags $1, \ldots, 4$ of Δp_t (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the "lag-length" parameter equal to four: * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Sum of coefficients on Δp_{t-s}, $s = 1, \ldots, 4$.

calculate the time-series evolution of the response coefficients associated with economic slack, as implied by the estimates of coefficients λ_1 and λ_2 reported in Tables 5 and 6 and the trajectory of the U.S. trade share shown in Figure 6. We then plot these estimates, as dashed lines in Figures 4 and 5, next to their corresponding time-varying estimates based on the 15-year rolling window. The comparison of solid and dashed lines in the panels of these two figures shows that this specific parametrization of the time-varying slope of the Phillips curve—a simple interaction between the trade share and economic slack—can account for about one-half of the decline in the responsiveness of PPI and CPI inflation to economic slack observed over the past 50 years. In addition, this interaction effect captures remarkably well the attenuation in the response of core PPI inflation to changes in economic slack that we observe during the latter part of the sample period.

3 Industry-Level Phillips Curve

The combination of a rising trade share with the concomitant decline in the responsiveness of aggregate inflation to fluctuations in economic activity provides suggestive evidence that the observed flattening of the Phillips curve is at least partly due to increased trade intensity of the U.S. economy. The variation used to estimate this effect, however, relies solely on the secular increase in the U.S. trade share over the past 50 years or so and moreover does not fully explain the substantial reduction in the estimated slope of the aggregate Phillips curve. To provide a more thorough analysis of this phenomenon, we now turn to industry-level data, where we can exploit variation in trade shares across industries to test whether a differential trade exposure influences the sensitivity of inflation to economic slack.

3.1 Data Sources and Methods

To construct the panel data set used in this analysis, we utilize the most detailed (i.e., 6-digit NAICS) industry-level PPIs published by the Bureau of Labor Statistics, which we merge with the corresponding industry-level data on industrial production—a measure of output—constructed by the Federal Reserve.[13] The resulting data set covers all 6-digit NAICS industries—excluding those in the Utilities sector (i.e., 2-digit NAICS code 22)—that are used to produce both the producer price and industrial production indexes for the U.S. economy. The industry-level price and production data are available at the monthly frequency, and we convert them to quarterly frequency by simply averaging the values of each index over the three months of each quarter.

The industry-level price and production data are available starting in the early 1970s. However, the data are not available for every industry from the beginning—that is, the panel is unbalanced—and there is an especially large expansion in the number of industries covered that occurred in the mid-1980s. To capture this broad array of industries, we thus begin our sample in 1984:Q1. All told, our unbalanced panel includes price and production data for 319 industries at the 6-digit NAICS level, covering the period from 1984:Q1 to 2017:Q4. We complement these industry-level data on output and prices, with the corresponding data on wages and employment from the Quarterly Census of Employment and Wages (QCEW), a data collection program that publishes a quarterly count of employment, total wages, and average weekly wages per employee, reported by companies

[13] Industrial production indexes are not available for the full set of 6-digit NAICS industries. At such a fine level of disaggregation, there are in some cases an insufficient number of production units to construct a meaningful estimate of the index. In those instances, the staff at the Federal Reserve Board aggregates the underlying data across several of such closely related industries. In our matching algorithm, we assigned such industrial production data to all the 6-digit industries in the index.

covering more than 95 percent of U.S. jobs. The QCEW data, however, are available only starting in 1990:Q1. We thus also consider a more in-depth analysis using a balanced panel of 185 industries for which all of these variables are available over the 1990:Q1–2017:Q4 period.[14]

To measure trade exposure at the industry level, we rely on the annual (nominal) import and export data, which are made available by the Center for International Data at University of California Davis and cover the period from 1972 to 2006.[15] The data provided are disaggregated by country (source for imports and destination for exports) and Schedule B number. These data were first aggregated to the total annual imports and exports at the industry level using the 5-digit Standard Industrial Classification (SIC) codes. The annual (nominal) imports and exports for the 2007–2017 period were obtained from the U.S. Census Bureau's USA Trade Online database and are available at the 10-digit Harmonized System Code (HTS) level. Using various crosswalks, all of these data had to be first mapped to industries at the 6-digit NAICS level. At such a fine level of disaggregation, however, there are numerous missing industry/year observations. Accordingly, we aggregated trade date to the 4-digit NAICS level. The resulting panel data set was then merged with the annual 4-digit NAICS data on (nominal) value-added output provided by the Bureau of Economic Analysis; these data were then used to calculate trade exposure—the sum of imports and exports relative to output—for each 4-digit NAICS industry.

The solid line in Panel A of Figure 7 shows the time-series evolution of the (unweighted) cross-sectional median of the four-quarter percent change in PPI inflation across 319 industries in our unbalanced panel, while the shaded band depicts the corresponding (unweighted) interquartile range. The dashed line, in contrast, shows the four-quarter percent change based on the published core PPI. In Panel B, the solid line and the shaded band depict the same moments of the four-quarter percent change in industrial production across the same set of industries, while the dashed line shows the corresponding growth rate of total industrial production. As evidenced by the shaded bands, the inflation rates and output growth vary significantly across industries. At the same time, the time-series fluctuations in the two medians closely match dynamics of their corresponding aggregates, an indication that our industry-level data are representative of the economy as a whole.

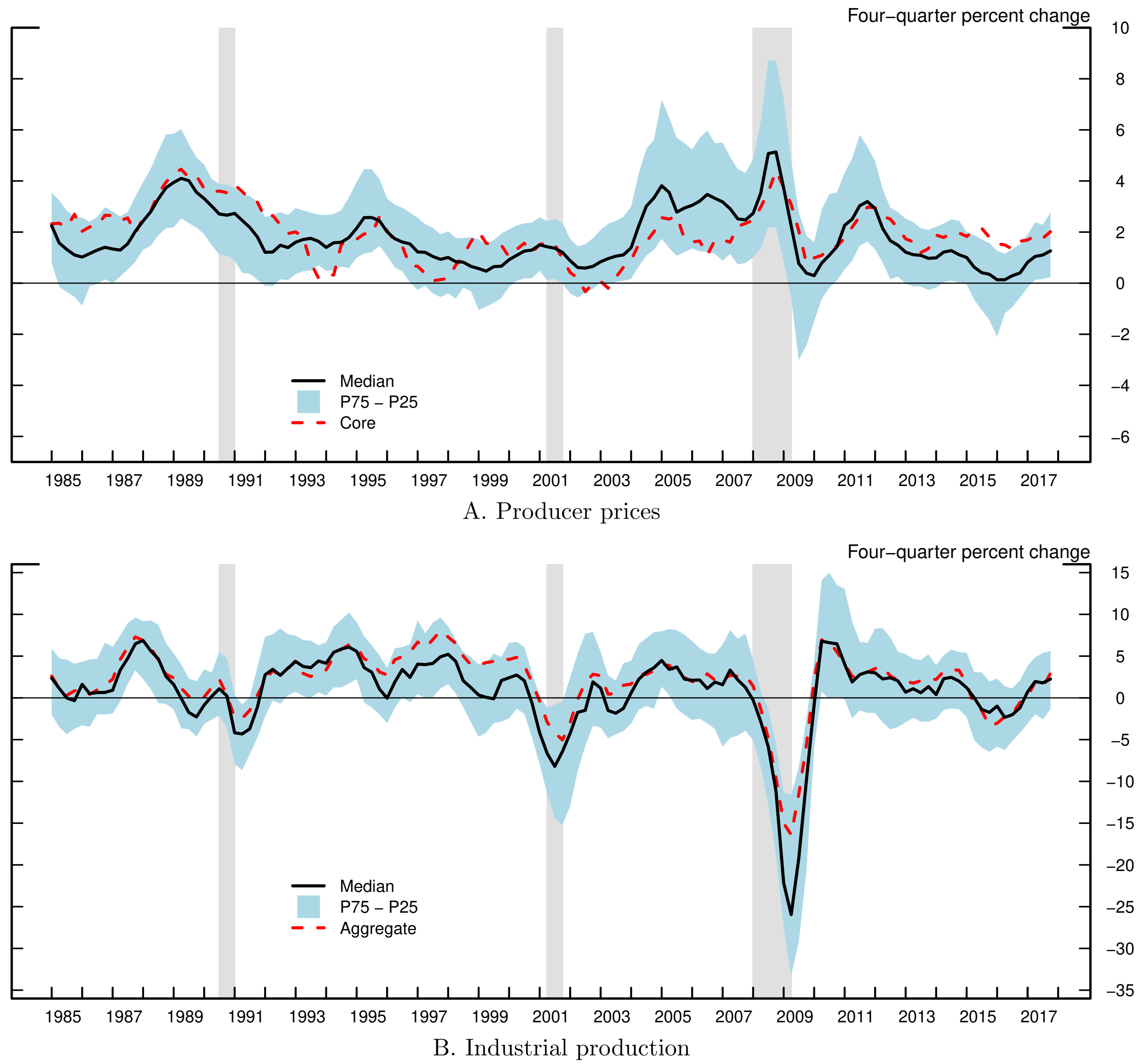
3.2 Baseline Estimates

To analyze the relationship between producer prices and economic activity at the industry level, we reformulate our baseline Phillips curve specification given by equation (1) above to accommodate the cross-sectional aspect of the industry-level data. Specifically, we estimate the following panel-

[14]The industry-level data exhibit significant seasonal fluctuations. Accordingly, we filtered all industry-level variables using the Census Bureau's X12 seasonal adjustment procedure—thus all of our growth rates (i.e., log differences) are constructed using seasonally adjusted level series. To ensure that our results were not influenced by a small number of extreme observations, all quarterly growth rates were winsorized at the 0.5th and 99.5th percentiles.

[15]These data were assembled by Robert Feenstra through the projected funded by a grant from the National Science Foundation to the NBER; see http://cid.econ.ucdavis.edu/usix.html for further details.

Figure 7: Industry-Specific Producer Prices and Industrial Production



Note: All industry-specific price and industrial production indexes are seasonally adjusted. The solid lines depict the cross-sectional medians of the specified series, while the shaded bands depict the corresponding interquartile ($P75 - P25$) ranges. The shaded vertical bars denote the NBER-dated recessions.
Source: Authors' calculations using data from the Bureau of Labor Statistics; and Federal Reserve Board.

data version of the Phillips curve:

$$\Delta_{h+1} p_{i,t+h} = \lambda \text{gap}_{it} + \sum_{s=1}^{4} \phi_s \Delta p_{i,t-s} + \mu_i + \eta_t + \epsilon_{i,t+h}, \tag{4}$$

where p_{it} denotes the logarithm of the producer price index for industry i in quarter t and gap_{it} is a measure of economic slack (or activity) in that industry. This specification also allows for

Table 7: Industry-Level Phillips Curve

	Sample: 1984:Q1–2017:Q4		Sample: 1998:Q1–2017:Q4	
Explanatory Variables	(1)	(2)	(3)	(4)
$[q_{it} - \tilde{q}_{it}]$	0.014**	.	0.020***	.
	(0.006)		(0.007)	
$\Delta_4 q_{it}$	.	0.027***	.	0.030***
		(0.008)		(0.008)
Sum: inflation lags[a]	−0.057*	−0.054*	−0.082**	−0.079**
	(0.031)	(0.030)	(0.037)	(0.037)
Adj. R^2	0.220	0.222	0.246	0.246
Panel Dimensions				
No. of industries	319	319	319	319
Avg. T_i (quarters)	95.6	95.8	60.4	60.5
Obs.	30,512	30,566	19,266	19,287

Note: The dependent variable in each Phillips curve specification is $\Delta_5 p_{i,t+4}$, the annualized log-difference in industry-specific producer price index from date $t-1$ to date $t+4$. Explanatory variables: $[q_{it} - \tilde{q}_{it}]$ = industry-specific industrial production gap; and $\Delta_4 q_{it}$ = log-difference in industry-specific industrial production index from date $t-4$ to date t. All specifications include industry and time fixed effects and lags $1, \ldots, 4$ of Δp_{it} (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are clustered across industries and time, according to Cameron et al. (2011): * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] Sum of coefficients on $\Delta p_{i,t-s}$, $s = 1, \ldots, 4$.

an industry-specific intercept μ_i that is estimated using industry fixed effects and a full set of time dummies—denoted by η_t, $t = 1, 2, \ldots, T$—that capture variation in common factors across industries. To measure the extent of resource utilization within each industry, we compute the "industrial production" gaps for each industry—denoted by $[q_{it} - \tilde{q}_{it}]$—as (100 times) the log-deviation of industrial production index (q_{it}) from its stochastic trend ($\tilde{q}_{it}$), where the latter is estimated using the Hamilton (2017) filter. As an alternative, we also consider a simple four-quarter log-difference of industrial production, denoted by $\Delta_4 q_{it}$.

Columns (1) and (2) of Table 7 report estimates of the Phillips curve at the four-quarter horizon (i.e., $h = 4$) for the full sample of industries from 1984:Q1 to 2017:Q4. Columns (3) and (4), on the other hand, provide comparable estimates for a subsample based on the 1998:Q1–2017:Q4 period, which corresponds to the time period in which the slope of the aggregate Phillips curve for PPI inflation is estimated to have have stabilized near zero (see Figure 4).[16]. According to columns (1) and (2), fluctuations in economic activity—measured either as deviations of industrial output from its trend or as four-quarter growth in output—are important determinants of producer price inflation at the industry level. Although precisely estimated, the economic magnitudes of these coefficients are fairly small: An increase in the industrial production gap of 10 percentage points in quarter t—an increase of a bit less than one standard deviation—is estimated to boost annualized

[16]Because our panel data set is unbalanced, the coefficient estimates are not strictly comparable across these two periods.

PPI inflation from quarter $t-1$ to $t+4$ a mere 15 basis points; the same-sized increase in the four-quarter growth of industrial output leads to a rise in PPI inflation of about a quarter of a percentage point over the same horizon.

While small in economic terms, these estimates are nonetheless broadly consistent with those based on the aggregate time-series data. For example, the coefficient on the output gap in the aggregate Phillips curve for core producer prices estimated over the 1984:Q1–2017:Q4 period is 0.063 (std. error = 0.054), while the corresponding coefficient estimate based on the 1998:Q1–2017:Q4 sample is -0.021 (std. error = 0.056). In other words, the slope of the aggregate Phillips curve for core PPI inflation is statistically indistinguishable from zero over this period. It is also worth noting that the estimates of coefficients on economic activity reported in Table 7 are remarkably stable across the two sample periods. Thus, the industry-level estimates of the response of PPI inflation to fluctuations in industrial output do not show the same kind of attenuation pattern that we estimate using the aggregate time-series data.

We next examine whether the responsiveness of PPI inflation to fluctuations in economic activity at the industry level varies with the state of aggregate economy. To do so, we consider a variant of specification (4), which also includes an interaction between the industry-specific indicators of economic activity—$[q_{it} - \tilde{q}_{it}]$ or $\Delta_4 q_{it}$—and the state of aggregate economy. We measure the latter in a continuous way by the aggregate output gap, $[y_t - y_t^*]$, or in a discrete manner by an indicator variable $\mathbf{1}[S_t \gtrless 0]$, where $S_t < 0$ when $[y_t - y_t^*] > 0$ or $[U_t - U_t^*] < 0$ and $S_t > 0$ when $[y_t - y_t^*] < 0$ or $[U_t - U_t^*] > 0$; that is, $S_t < 0$ indicates resource over-utilization in the economy, while $S_t > 0$ corresponds to an aggregate state of resource under-utilization.

The results of this exercise for our unbalanced panel of industries over the full sample period are reported in Table 8. According to the entries in the table, the slope of the industry-level Phillips curve depends on aggregate economic conditions. When using $[q_{it} - \tilde{q}_{it}]$ to measures slack at the industry level (column 1), the coefficient on the interaction term $[q_{it} - \tilde{q}_{it}] \times [y_t - y_t^*]$ is negative, implying a reduced sensitivity of industry-level PPI inflation to changes in the industry-level slack when aggregate GDP is above its potential and vice versa. For example, when the aggregate output gap is at the 5th percentile of its distribution, the slope of the industry-level Phillips curve is estimated to be 0.031 (std. error = 0.001), whereas at the 95th percentile, the estimated slope is economically and statistically indistinguishable from zero.

A very similar result emerges when the aggregate state can take on only two values (column 2): The coefficient on $[q_{it} - \tilde{q}_{it}]$ is positive and statistically highly significant only when $S_t < 0$, that is, in periods of aggregate resource under-utilization; when $S_t > 0$, however, industry-level PPI inflation exhibits no sensitivity to changes in the industrial production gap. As shown in columns (3) and (4), these findings are robust to using the four-quarter growth in industrial output as a measure of cyclical resource utilization at the industry level. More generally, the results in Table 8 appear to be at odds with those for the aggregate PPI inflation reported in Table 3, which indicate a much greater responsiveness of PPI inflation—both headline and core—to changes in economic slack in periods of aggregate resource over-utilization. This discrepancy, however, likely reflects differences

Table 8: Asymmetric Industry-Level Phillips Curve

Explanatory Variables	(1)	(2)	(3)	(4)
$[q_{it} - \tilde{q}_t]$	0.009	.	.	.
	(0.006)			
$[q_{it} - \tilde{q}_{it}] \times [y_t - y_t^*]$	-0.005^{**}	.		.
	(0.002)			
$[q_{it} - \tilde{q}_{it}] \times \mathbf{1}[S_t < 0]$	.	0.021^{***}	.	.
		(0.008)		
$[q_{it} - \tilde{q}_{it}] \times \mathbf{1}[S_t > 0]$	.	0.000	.	.
		(0.008)		
$\Delta_4 q_{it}$	.	.	0.026^{***}	.
			(0.008)	
$\Delta_4 q_{it} \times [y_t - y_t^*]$	.	.	-0.002	.
			(0.002)	
$\Delta_4 q_{it} \times \mathbf{1}[S_t < 0]$	.	.	.	0.035^{***}
				(0.008)
$\Delta_4 q_{it} \times \mathbf{1}[S_t > 0]$	.	.	.	0.015
		.		(0.011)
$\Pr > W$[a]	.	0.044	.	0.047
Effect at $P5$[b]	0.031^{***}	.	0.032^{***}	.
	(0.011)		(0.009)	
Effect at $P95$[c]	-0.004	.	0.021	.
	(0.008)		(0.012)	
Sum: inflation lags[d]	-0.057^{*}	-0.057^{*}	-0.055^{*}	-0.054^{*}
	(0.031)	(0.031)	(0.030)	(0.030)
Adj. R^2	0.221	0.221	0.221	0.222

Note: Sample: an unbalanced panel of 319 industries from 1984:Q1 to 2017:Q4. The dependent variable in each Phillips curve specification is $\Delta_5 p_{i,t+4}$, the annualized log-difference in industry-specific producer price index from date $t-1$ to date $t+4$. Explanatory variables: $[q_{it} - \tilde{q}_{it}]$ = industry-specific industrial production gap; $\Delta_4 q_{it}$ = log-difference in industry-specific industrial production index from date $t-4$ to date t; $[y_t - y_t^*]$ = aggregate output gap; and $\mathbf{1}[S_t \gtrless 0]$ = indicator variable describing the state of aggregate economy, with $S_t < 0$ indicating negative economic slack and $S_t > 0$ indicating positive economic slack (see the text for details). All specifications include industry and time fixed effects and lags $1, \ldots, 4$ of Δp_{it} (not reported) and are estimated by OLS. Asymptotic standard errors reported in parentheses are clustered across industries and time, according to Cameron et al. (2011): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] p-value for the test of equality of coefficients on positive and negative indicators of aggregate economic slack.

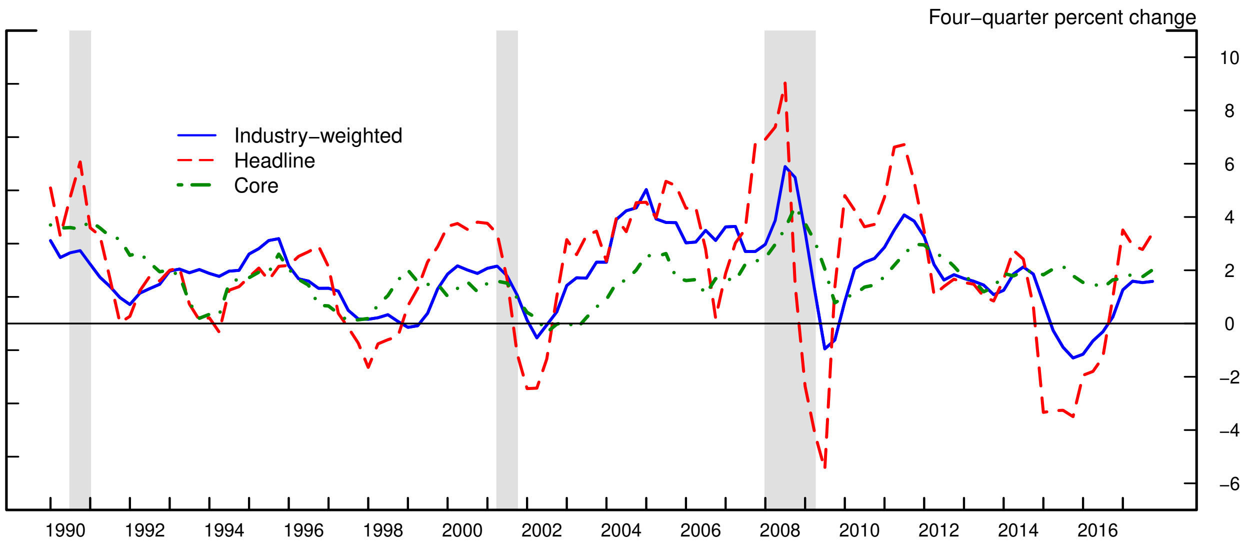
[b] The average marginal effect of $\Delta_4 q_{it}$ or $[q_{it} - \tilde{q}_{it}]$ when the aggregate output gap is at the 5th percentile of its sample distribution.

[c] The average marginal effect of $\Delta_4 q_{it}$ or $[q_{it} - \tilde{q}_{it}]$ when the aggregate output gap is at the 95th percentile of its sample distribution.

[d] Sum of coefficients on $\Delta p_{i,t-s}$, $s = 1, \ldots, 4$.

in the sample periods between these two exercises, as the asymmetry in the aggregate Phillips curve for PPI inflation is noticeably less pronounced in the post-1984 data. In combination, these findings suggest that the slope of the Phillips curve may change in response to the frequency and the type of shocks—aggregate demand vs. aggregate supply—that economy may be experiencing

Figure 8: Industry vs. Aggregate Producer Price Inflation



Note: The solid line depicts a weighted average of producer price inflation across 185 industries, with weights equal to the corresponding average industry-specific employment shares. The dashed (dotted) line depicts the overall (core) producer price inflation. The shaded vertical bars denote the NBER-dated recessions.
Source: Authors' calculations using data from the Bureau of Labor Statistics.

at any given time.

3.3 The Role of the Trade Share

With these results in hand, we now return to the question of whether differences in external trade exposure across industries influence the sensitivity of PPI inflation to economic slack. A straightforward way to test this hypothesis would be to estimate our baseline industry-level Phillips curve given in equation (4) on a sample of "low" trade intensity industries and compare the results with those based on a sample of "high" trade intensity industries. However, to make a statement of whether differences in trade exposure across industries matter in the aggregate, we must specify some kind of a weighting scheme.[17] Unfortunately, the value of shipments, which would provide an economically most sensible weighting scheme for the industry-specific inflation rates, are not available at the 6-digit NAICS level. As an alternative, we rely on the QCEW employment data and aggregate the industry-specific PPI inflation rates using the industry-specific *average* employment shares as weights. Because the employment data are available only starting in 1990:Q1, we restrict the analysis to the balanced panel of 185 industries, which ensures that our aggregation scheme is not affected by changes in the composition of industries over time.

To gauge the reasonableness of our aggregation scheme, the solid line in Figure 8 shows the time-series evolution of a weighted cross-sectional average of four-quarter PPI inflation rates across

[17]Note that in the above regression analysis, each industry received an equal weight. As such, the results in Tables 7 and 8 may not provide an accurate picture of the aggregate relationship between inflation and economic slack that is central to our analysis.

Table 9: Industry-Level Phillips Curve and the Trade Share
(Weighted vs. Unweighted Estimates)

	Industry Category		
Explanatory Variables	All	Low Trade Shr.	High Trade Shr.
A. Weighted Estimates			
$[q_{it} - \tilde{q}_{it}]$	0.015	0.029***	0.006
	(0.010)	(0.011)	(0.011)
Sum: inflation lags[d]	−0.060	−0.159***	0.044
	(0.041)	(0.043)	(0.043)
Adj. R^2	0.243	0.228	0.306
B. Unweighted Estimates			
$[q_{it} - \tilde{q}_{it}]$	0.025***	0.035***	0.014**
	(0.007)	(0.013)	(0.006)
Sum: inflation lags[d]	−0.060	−0.091**	0.004
	(0.036)	(0.042)	(0.045)
Adj. R^2	0.198	0.198	0.227

Note: Sample: a balanced panel of 185 industries from 1990:Q1 to 2017:Q4 (Obs. = 19,239). The dependent variable in each Phillips curve specification is $\Delta_5 p_{i,t+4}$, the annualized log-difference in industry-specific producer price index from date $t-1$ to date $t+4$. Explanatory variables: $[q_{it} - \tilde{q}_{it}]$ = industry-specific industrial production gap. All specifications include industry and time fixed effects and lags $1, \ldots, 4$ of Δp_{it} (not reported). In Panel A, the specifications are estimated by WLS—using average industry employment shares as weights—while in Panel B they are estimated by OLS. Asymptotic standard errors reported in parentheses are clustered across industries and time, according to Cameron et al. (2011): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Sum of coefficients on $\Delta p_{i,t-s}$, $s = 1, \ldots, 4$.

the 185 industries in our balanced panel, while the dashed and dashed-dotted lines show the corresponding behavior of the headline and core producer price inflation, respectively. As can be seen from the figure, our employment-weighted aggregate inflation broadly tracks a mix of the headline and core PPI inflation. It is clearly more cyclical than the core inflation and somewhat less cyclical than the headline inflation. Importantly, this aggregation exercise gives us confidence that an employment-weighted version of the 6-digit industry data captures the cyclical variation that we see in other time-series aggregates and hence provides a meaningful laboratory from which one can infer aggregate phenomena from the industry-level estimates.

We use the balanced panel—with the associated average employment shares—to examine the extent to which the responsiveness of inflation to fluctuations in economic activity differs with the degree of trade intensity across industries. As noted above, we split our sample of 185 industries into two groups, based on whether their average trade share is above or below 5 percent. This cutoff corresponds to the median of the industry-specific average trade shares, weighted by the industry-specific average employment shares, and implies that the low and high trade intensity industry groups each account for about one-half of total employment in our balanced panel.

Table 9 reports the results of this exercise for inflation at the four-quarter horizon (i.e., $h = 4$)

and using the industrial production gap, $[q_{it} - \tilde{q}_{it}]$, to measure slack at the industry level. In the first column of Panel A, we report the WLS estimates of the coefficient on the industrial production gap for all industries, while in the second and third column, we report the corresponding WLS estimates for low and high trade share industry groupings, respectively; for comparison purposes, Panel B contains the corresponding OLS estimates, which weigh all industries equally.

The WLS estimate of the coefficient on economic slack for all industries is a bit smaller than its corresponding OLS estimate—0.015 vs. 0.025—and also less precisely estimated. More importantly, the WLS estimates of coefficients on economic slack show a clear difference across the two industry groupings: In low trade intensity industries, the coefficient on economic slack is positive and statistically highly significant, whereas in high trade intensity industries, the coefficient on economic slack is essentially zero, in both economic and statistical terms. These results provide further support for the argument that globalization and increased international trade may be responsible, at least in part, for the observed attenuation in the response of inflation to fluctuations in economic activity. However, swings in producer prices at the industry level are far more likely to reflect a confluence of demand shocks—which push prices and output in the same direction—and supply shocks, which push them in opposite directions. Thus one should be cautious in providing a structural interpretation to the coefficient estimates reported in Table 9.

4 Trade Share and the Effects of Aggregate Shocks

In this section, we employ an alternative approach to investigate the role that international trade may play in determining domestic inflation outcomes. Specifically, we identify aggregate shocks that simultaneously influence inflation and output dynamics and trace out their effects on industry-level outcomes. We then examine the extent to which the industry-level responses of prices, wages, output, and employment to such aggregate shocks differ across industries with a differential exposure to international trade and thus to global factors.

4.1 Econometric Methodology

As in the previous section, we focus on a balanced panel of 185 industries for which all variables are available over the 1990:Q1–2017:Q4 sample period. Given the high dimensionality—in both the cross-sectional and time-series dimensions—of our industry-level data, we use the FAVAR methodology proposed by Bernanke and Boivin (2003) Bernanke et al. (2005) to identify aggregate shocks and trace out their effect on price and wage inflation and the growth of output and employment at the industry level. To identify aggregate shocks of interest, we study the response of industry-level variables to both a sudden deterioration in broad domestic financial conditions and an unanticipated increase in commodity prices. The adverse shock to financial conditions may be broadly interpreted as a reduction in aggregate demand, while the commodity price shocks arguably capture mostly supply-side considerations. Both of these two types of disturbances have featured prominently in recent discussions regarding the source of business cycle fluctuations over the time period under our consideration (see Stock and Watson, 2012).

Our estimation and identification procedure broadly follows the empirical methodology outlined in Gilchrist et al. (2009). In particular, we combine the industry-level data on price and wage inflation and on the growth of output and employment in an $(n_1 \times 1)$-dimensional vector X_{1t}.[18] We then consider a set of macro-level variables that summarize either domestic financial conditions or price developments in global commodity markets—these series are combined in an $(n_2 \times 1)$-dimensional vector X_{2t}. This data-rich environment can be succinctly represented by an $(n \times 1)$-dimensional vector $X_t = [X_{1t}' \; X_{2t}']'$, where $n = n_1 + n_2$ and $t = 1, 2, \dots, T$. We assume that X_t has a (linear) factor structure, whereby $X_{it} = \lambda_i' F_t + \nu_{it}$, $i = 1, \dots, n$, where F_t is a $(k \times 1)$-dimensional vector of common latent factors (with $k \ll n$), λ_i is the corresponding vector of factor loadings, and ν_{it} is an idiosyncratic random disturbance that is assumed to be uncorrelated across i and t.

When analyzing the dynamic effects of aggregate shocks, we assume that a subset of these common factors—denoted by a $(k_2 \times 1)$-dimensional vector F_{2t}—are factors that are specific to the aggregate variables contained in the vector X_{2t}. These factors do not contemporaneously influence the industry-level variables in the vector X_{1t}, but they do affect contemporaneously the variables in the vector X_{2t}. The rest of the factors—denoted by a $(k_1 \times 1)$-dimensional vector F_{1t}, where $k = k_1 + k_2$—are assumed to span the information contained in the entire data vector X_t. The relationship between the observed variables and the unobserved factors is assumed to be linear and is given by the following system of measurement equations:

$$\begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} \Lambda_{1,1} & \Lambda_{1,2} \\ \Lambda_{2,1} & \Lambda_{2,2} \end{bmatrix} \begin{bmatrix} F_{1t} \\ F_{2t} \end{bmatrix} + \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix}, \tag{5}$$

where

$$\Lambda = \begin{bmatrix} \Lambda_{1,1} & \Lambda_{1,2} \\ \Lambda_{2,1} & \Lambda_{2,2} \end{bmatrix}$$

is an $(n \times k)$ matrix of factor loadings.

The latent factors are assumed to follow a vector autoregressive process of the form:

$$\begin{bmatrix} F_{1t} \\ F_{2t} \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{1,t-1} \\ F_{2,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}, \tag{6}$$

where $\Phi(L)$ is a matrix lag-polynomial of finite order p. As it is standard in these models, we assume that $E[\nu_{it}\epsilon_{st}] = 0$, for all $i = 1, 2, \dots, n$ and $s = 1, 2, \dots, k$; and $E[\epsilon_{it}\epsilon_{jt}] = 0$, for all $i \neq j$. In this form, our model constitutes a static representation of a dynamic factor model (see Stock and Watson, 2010a); it is static in the sense that factors enter only contemporaneously in the system of measurement equations (5).

To identify the aggregate factors F_{2t}, we impose the following restrictions on the system of measurement equations. First, we assume that $\Lambda_{1,2} = 0$. This restriction on the factor loading

[18] Note that $n_1 = 4 \times 185 = 740$; that is, four series for each of the 185 industries.

matrix Λ implies that once we have conditioned on the factors F_{1t}, the remaining variation in the aggregate block X_{2t} has a systematic component that is reflected in its own factor structure. Although the aggregate factors F_{2t} have no contemporaneous effect on the vector X_{1t}, they affect the factors F_{1t} and, by extension, the variables in the industry block X_{1t} with a lag through the autoregressive dynamics of equation (6). The second identifying assumption is that the factors F_{1t} and F_{2t} are orthogonal, an assumption that separates the residual information content in the aggregate block from the factors summarizing the state of the economy, as measured by the full set of industry-specific information contained in the vector X_{1t}.[19]

To maintain an identification strategy that favors neither financial or commodity price shocks, we estimate two separate FAVAR specifications. In the first, the vector X_{2t} includes a broad array of domestic financial indicators, whereas in the second, the vector X_{2t} contains solely returns on key global commodities. Specifically, when considering how financial shocks affect industry-level outcomes, the vector X_{2t} consists of the following five financial indicators: the GZ corporate bond credit spread and the associated excess bond premium (see Gilchrist and Zakrajšek, 2012); the Moody's Baa-Aaa corporate bond credit spread; the term spread measured as the difference in yields on the ten- and two-year U.S. Treasury coupon securities; and the option-implied volatility on the S&P 500 stock price index, the VIX. The GZ and Baa-Aaa credit spreads and the excess bond premium are widely used indicators of financial strains obtained from the corporate bond market. The VIX, on the other hand, is a measure of risk appetite in equity markets, while the term spread primarily reflects investors' appetite for duration risk. These five indicators provide a broad summary of domestic financial conditions that are entirely reliant on market prices and, therefore, should capture changes in broad financial conditions in a timely manner.

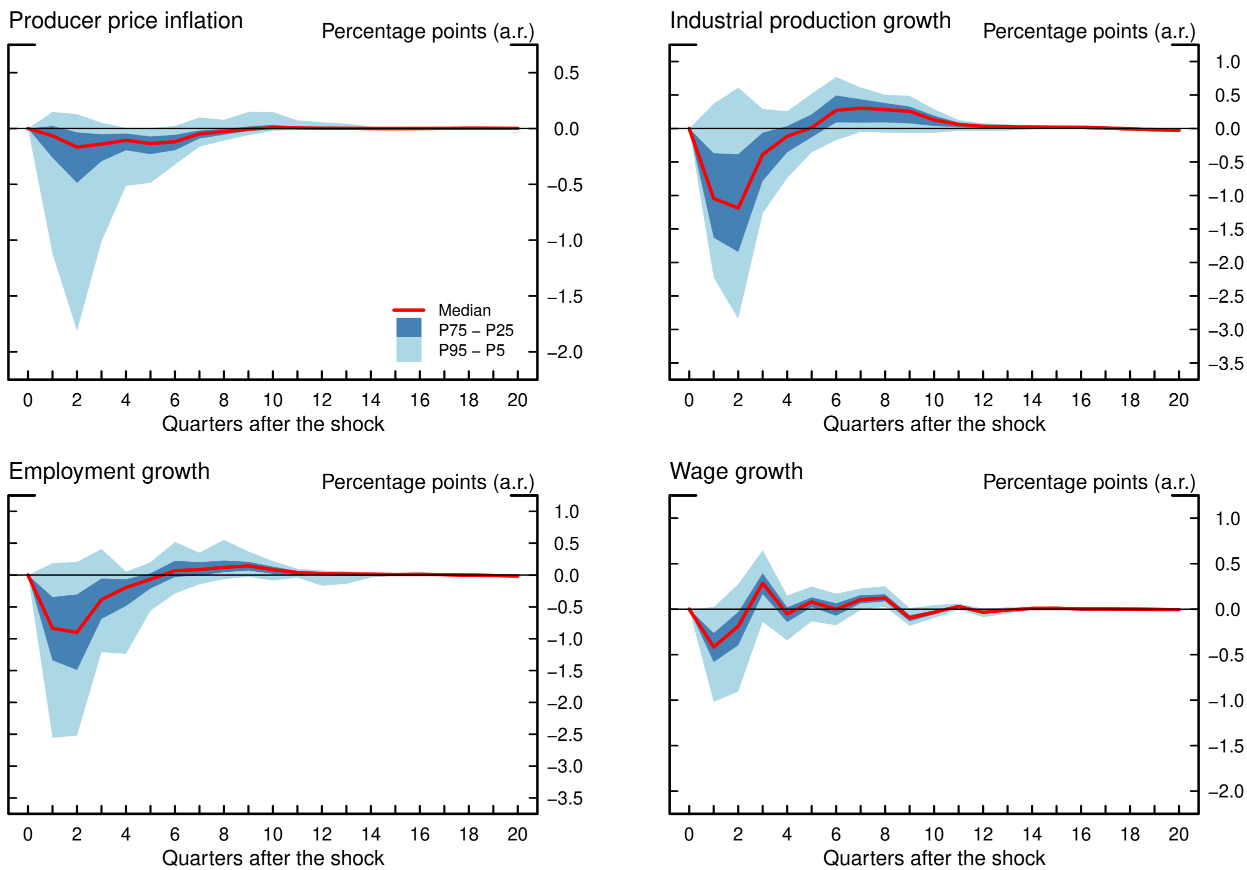
When considering the effect of shocks to commodity prices on industry-level outcomes, the vector X_{2t} consists of quarterly log-returns, calculated using ten price indexes (based on nominal U.S. dollars) for major commodities. These include the energy sector, beverages and three food-related sectors, fertilizer, timber and other raw materials, base metals, and precious metals.[20] In both FAVAR specifications, we allow for four common factors in the industry-level block X_{1t}—that is, $k_1 = 4$—and for one factor in the aggregate block X_{2t}, that is $k_2 = 1$. These choices were based on the information criteria proposed by Bai and Ng (2002); however, all of the results reported in this paper are robust to allowing a greater number of factors in either block.[21]

[19]We can estimate the FAVAR model given by equations (5) and (6) using a Gaussian maximum likelihood methods and Kalman filter to construct the likelihood function. However, in the presence of identifying assumptions with large n, this method is computationally demanding. We, therefore, follow the four-step procedure outlined in Gilchrist et al. (2009), as it is straightforward to implement and directly imposes the necessary identification restrictions.

[20]The monthly commodity price indexes for each of those commodity groupings were obtained from the World Bank's commodity price database "The Pink Sheet." For each index, the quarterly log-return was calculated using the monthly values of the index corresponding to the last month of each quarter.

[21]The presence of a single common factor in the cross-section of commodity prices is also consistent with the recent work of Delle Chiaie et al. (2017), who find that the bulk of fluctuations in commodity prices is well summarized by a single global factor.

FIGURE 9: Implications of an Adverse Financial Shock
(All Industries)



NOTE: The solid line in each panel depicts the median response of the specified variable to an adverse financial shock of one standard deviation across 185 industries; the shaded bands depict the corresponding $P75 - P25$ and $P95 - P5$ ranges.

4.2 Results

In this section, we present impulse responses of variables in the industry block X_{1t} to the two identified aggregate shocks. We first consider the dynamic effects of an adverse financial shock and then turn to results that examine the corresponding implications of a commodity price shock. We begin by reporting these baseline results for all industries. Lastly, we examine how international trade exposure influences industry-level inflation dynamics by dividing our sample of industries into those with a "low" trade exposure and those with a "high" trade exposure.

4.2.1 The Impact of Financial and Commodity Price Shocks

Figure 9 plots the distribution of industry-level outcomes in response to an adverse financial shock of one standard deviation in quarter zero. Though not shown, this shock causes a broad-based tightening of domestic financial conditions, implying an increase in the excess bond premium of about 30 basis points upon impact.[22] The solid line in each panel shows the median industry response of the specified variable to such a shock, while the dark shaded bands denote the range of responses between the 75th and 25th percentiles (the $P75 - P25$ range) and the light shaded bands denote the range of responses between the 95th and 5th percentiles (the $P95 - P5$ range). Recall that the factor F_{2t} is, by assumption, contemporaneously orthogonal to the variables in the industry block X_{1t} and thus aggregate shocks have has no effect on industry-level outcomes upon impact.

The identified financial shock is clearly contractionary—it induces a substantial decline in the growth of industrial production and employment for the median industry. A couple of quarters after its impact, this shock is cutting 1.2 percentage points from the annualized growth of output and 0.8 percentage points from the annualized growth of employment at the median. It also causes a significant step-down in both price and wage inflation: For the median industry, annualized price inflation is lowered 0.1 percentage points, whereas the reduction in annualized wage inflation is on the order of 0.4 percentage points. Notably, the reduction in the rate of growth of economic activity, prices, and wages occurs relatively quickly, peaking a mere two quarters after the shock. Economic growth remains depressed for several more quarters before recovering slowly, returning to its long-run level after about eight quarters. Judging by the shaded regions, the estimated range of industry responses implies that these effects are broad based. The combination of steep declines in the growth of output, employment, prices, and wages implies that the deterioration in broad domestic financial conditions delivers a response that is consistent with a reduction in aggregate demand within a New Keynesian framework.

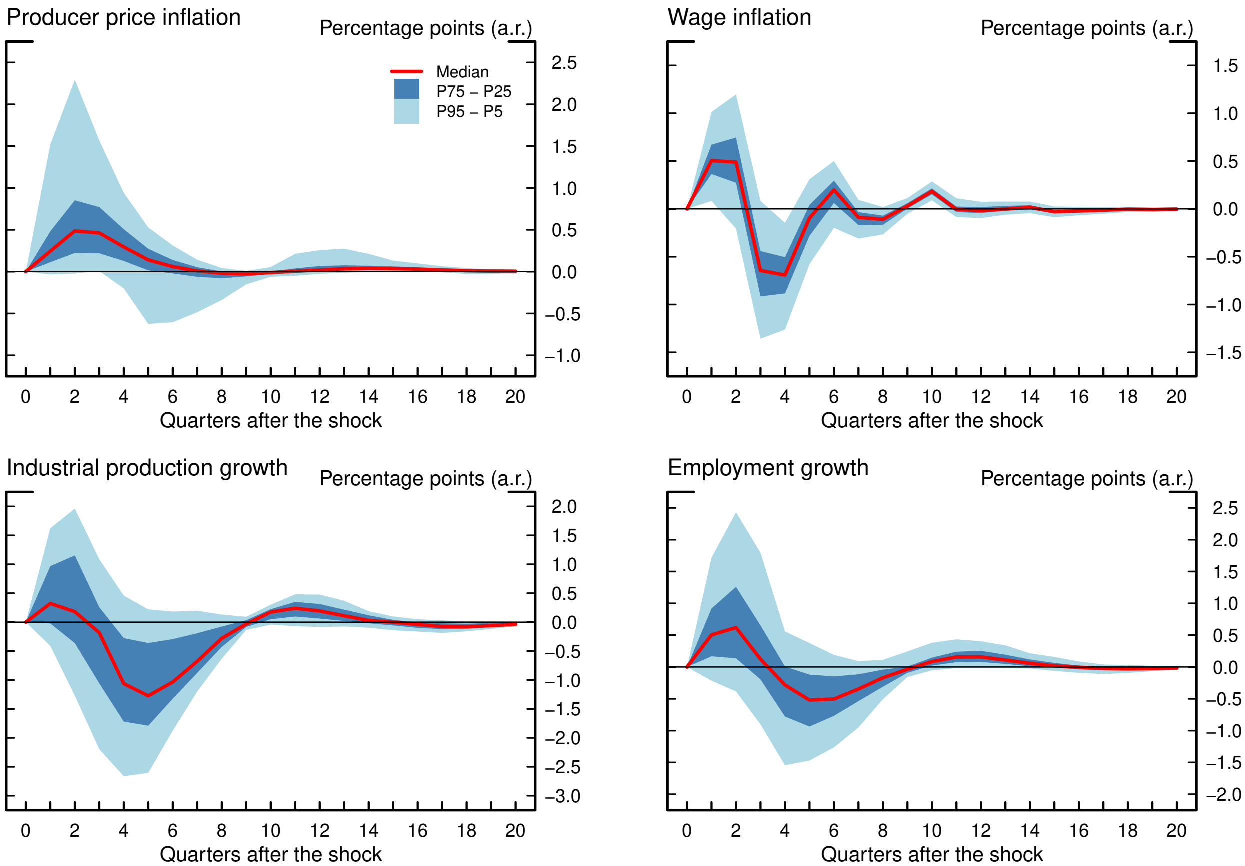
The same industry-level outcomes in response to an unanticipated one standard deviation increase in the factor driving commodity prices are shown in Figure 10. Such a commodity price shock, which causes a widespread increase in global commodity prices, leads to a sharp increase in producer price inflation across all industries. Interestingly, it also leads to a temporary surge in employment growth and wage inflation; output growth rises initially but then falls substantially. The rise in inflation, combined with the reduction in output growth, is consistent with the view that a commodity price shock is a negative supply shock to the U.S. industrial sector.

The temporary expansion in employment and the rise in wages, however, suggests a more nuanced interpretation. The initial increase in employment growth and wage inflation is consistent with the notion that firms—in response to a sudden increase in commodity prices—substitute away from materials and employ more labor. The rise in labor input in the immediate aftermath of a commodity price shock may also reflect the fact that our identification scheme does not fully separate demand and supply factors in response to broad-based fluctuations in commodity prices. In particular, the U.S. economy has in the past couple of decades become a substantial supplier of commodities, especially of energy, to the global market.

With these baseline results in hand, we now analyze the extent to which differential trade

[22] Over the 1990:Q1–2017:Q4 period, the standard deviation of the excess bond premium is about 50 basis points. As a point of comparison, the excess bond premium shot up more than 300 basis points following the collapse of Lehman Brothers in September 2008.

Figure 10: Implications of an Adverse Commodity Price Shock
(All Industries)

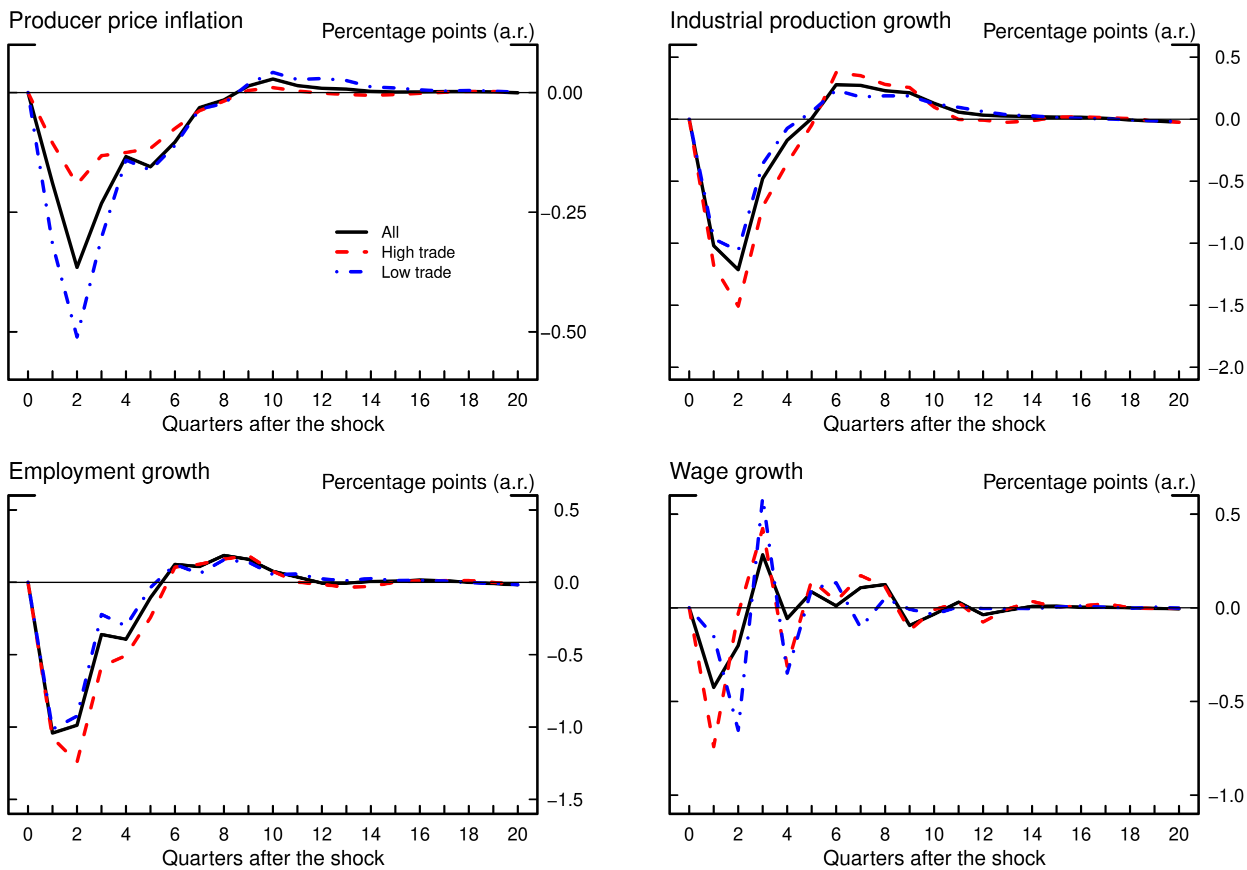


Note: The solid line in each panel depicts the median response of the specified variable to an adverse commodity price shock of one standard deviation across 185 industries; the shaded bands depict the corresponding $P75 - P25$ and $P95 - P5$ ranges.

exposure across industries changes the results reported above. As before, we sort our sample of industries based on their average trade exposure over the 1990:Q1–2017:Q4 period and group them into a low and high trade exposure categories. We then separately estimate our two FAVAR specifications for each of the two groupings, an approach that ensures that we do not artificially constrain the factor structure to be the same across industries with a differential trade exposure. As a reminder, recall that each category of industries accounts, on average, for about 50 percent of total employment in our sample.

Unlike our baseline exercise, this exercise is focused on the implications of the two shocks for aggregate outcomes. Specifically, for each industry-level endogenous variable, we compute a weighted average response across industries, where weights are equal to the industry-specific average employment shares within each group of industries (i.e., low vs. high trade exposure industry categories). In addition, we report the aggregate responses for all industries by weighting the industry-specific responses from Figures 9 and 10 with their corresponding average employment

Figure 11: Implications of an Adverse Financial Shock
(Low vs. High Trade Share Industries)



Note: The solid line in each panel depicts the employment-weighted average response of the specified variable to an adverse financial shock of one standard deviation across 185 industries; the dashed (dashed-dotted) lines depict the corresponding employment-weighted average responses for a subset of industries with a high (low) average trade share.

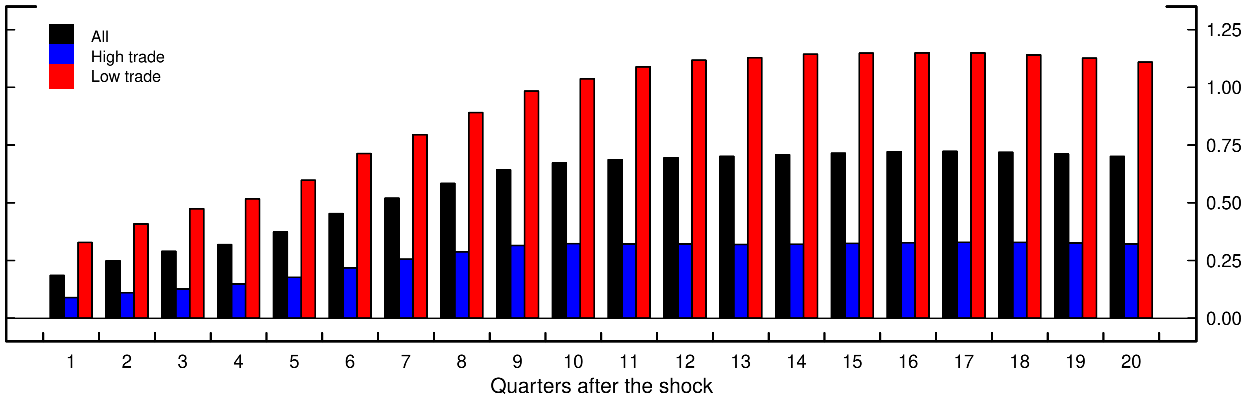
shares. These results, corresponding to the adverse financial shock, are shown in Figure 11, whereas those pertaining to the commodity price shock are shown in Figure 14.[23]

As shown by the solid lines in Figure 11, the aggregate responses of producer price and wage inflation and the growth of output and employment to an adverse financial shock follow closely the contours of the corresponding median industry-level responses shown in Figure 9: Price and wage inflation, along with output and employment growth, all fall sharply, with peak responses occurring one to two quarters after the impact of the shock; moreover, these aggregate responses remain persistently below their respective long-run values for six to eight quarters after the shock.

Note that the (absolute) magnitude of responses for the aggregates—as defined by the employment-weighted averages of industry-level responses—are somewhat larger than their cor-

[23]Figures A-1–A-2 and Figures A-3–A-4 in Appendix A show the industry-level responses for the low and high trade share industry categories when the economy is perturbed by an aggregate financial shock and a widespread unanticipated increase in commodity prices, respectively.

FIGURE 12: Sensitivity of Producer Prices to Output – Aggregate Demand Shocks (Low vs. High Trade Share Industries)



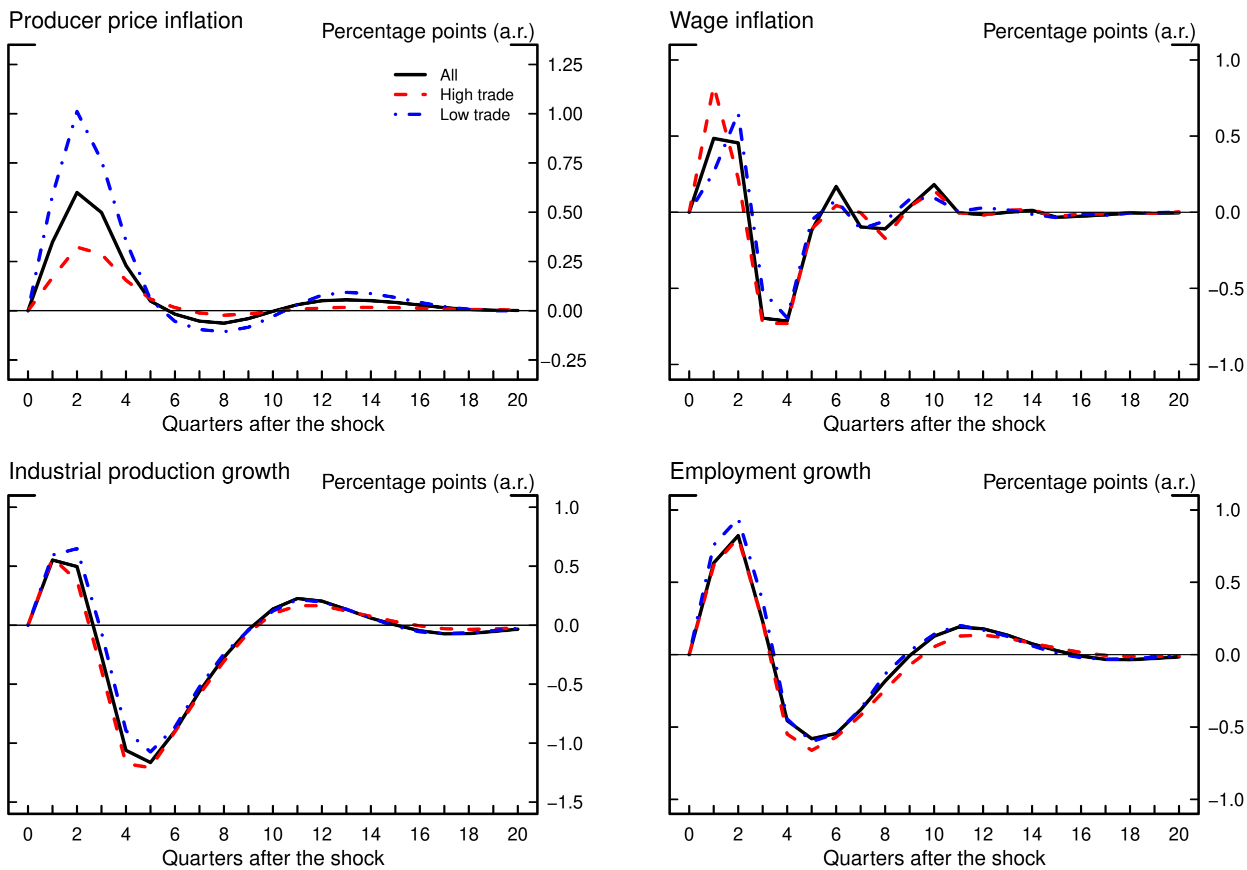
NOTE: The bars in the figure depict the estimated sensitivity of producer prices to fluctuations in output induced by aggregate financial shocks (see the text for details).

responding unweighted median responses across industries. In particular, the annualized output and employment growth both fall by more than one percentage point, while the annualized producer price inflation declines about 30 basis points. The estimated decline in the growth of output in response to a financial shock is consistent with other studies who find that such disturbances lead to a significant contraction in economic activity (see Gilchrist et al., 2009; Gilchrist and Zakrajšek, 2012; Boivin et al., 2018). That said, the estimated drop in producer price inflation is both larger and occurs more quickly than the one estimated by VARs that use aggregate time-series data. Overall, these results indicate that producer price inflation is fairly sensitive to fluctuations in economic activity induced by changes in broad financial conditions—producer price inflation declines roughly 25 basis points when a tightening of financial conditions induces a one percentage point decline in the growth of industrial output.

Figure 11 also displays the aggregate responses to an adverse financial shock for high and low trade industries. As shown in the upper left panel, the dynamics of inflation differ markedly across industries with a differential trade exposure. Notably, the peak decline in producer price inflation of 0.5 percentage points for industries with low trade exposure is more than three times as large as that for industries with high trade exposure. Although the unanticipated tightening of financial conditions causes a somewhat greater contraction in economic activity among high trade industries, the responses of output and employment growth are broadly similar—in terms of both timing and their magnitudes—across the two industry groupings. Wage inflation also behaves in a similar manner across these two industry groupings, though in high trade industries, the deceleration in wages occurs more quickly.

A useful way to highlight the difference in inflation dynamics between low and high trade industries is to compute the cumulative responses of price inflation and output growth. The ratio of the resulting price response to the output response then provides an estimate of the decline in

FIGURE 13: Implications of an Adverse Commodity Price Shock
(Low vs. High Trade Share Industries)

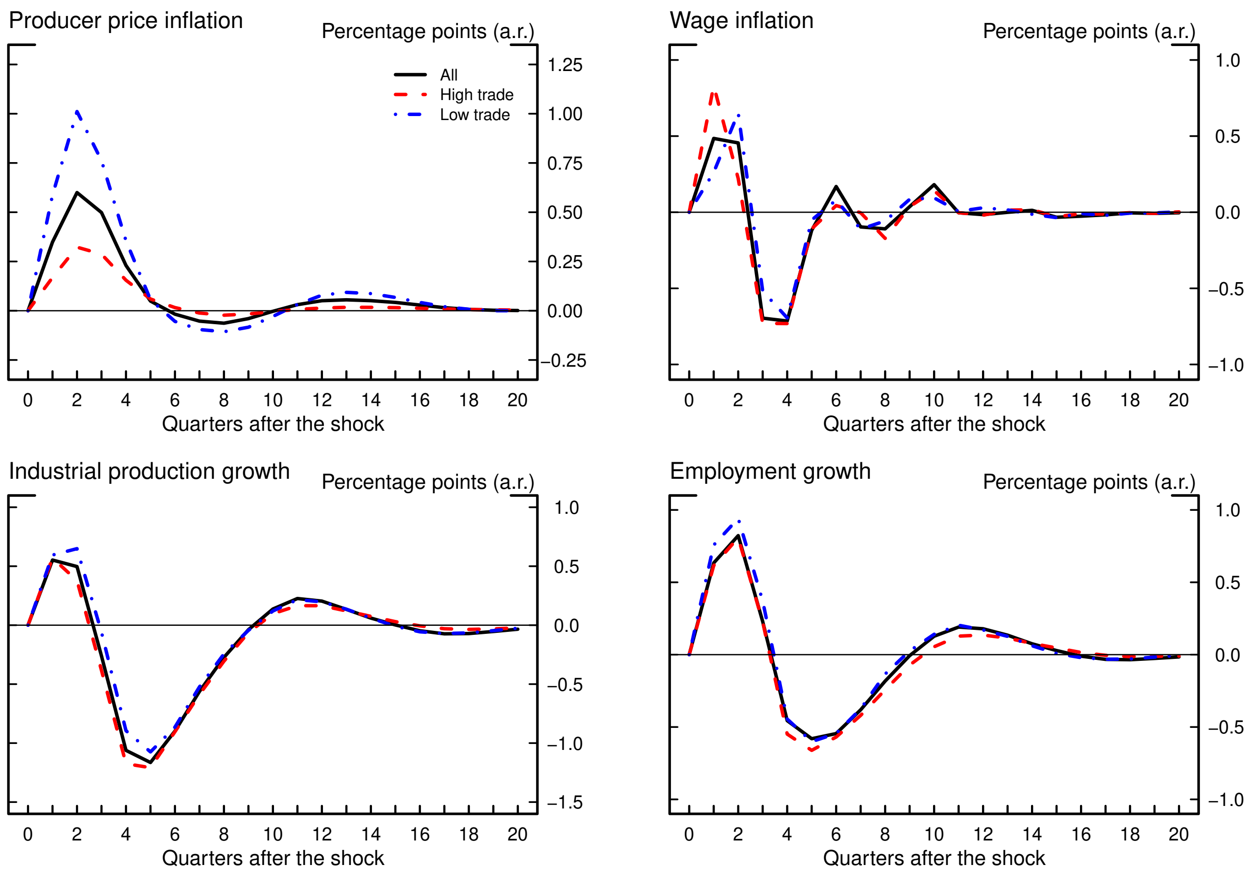


NOTE: The solid line in each panel depicts the employment-weighted average response of the specified variable to an adverse commodity price shock of one standard deviation across 185 industries; the dashed (dashed-dotted) lines depict the corresponding employment-weighted average responses for a subset of industries with a high (low) average trade share.

prices relative to output that occurs at different horizons in response to an adverse financial shock. As shown in Figure 12, in low trade intensity industries, producer prices are estimated to decline about 0.3 percent for every one percent decline in output at very short horizons and about one percent for the same-sized reduction in output at the two-year horizon. In high trade intensity industries, by contrast, producer prices are estimated to decline about 0.1 percent for a one percent reduction in output at very short horizons and about 0.3 percent at the two year horizon. In sum, these findings imply that the response of prices relative to output is—at every horizon—three times larger in low trade industries compared with their high trade counterparts.

Next, we examine how differences in trade exposure across industries affect the dynamics of aggregate producer price and wage inflation and economic activity in response to a commodity price shock. As before, we compute aggregate responses as a weighted average of industry-level responses, with weights equal to the industry-specific average employment shares within each group of industries. These results are shown in Figure 14. As in the case of a financial shock, the aggregate

Figure 14: Implications of an Adverse Commodity Price Shock
(Low vs. High Trade Share Industries)



Note: The solid line in each panel depicts the employment-weighted average response of the specified variable to an adverse commodity price shock of one standard deviation across 185 industries; the dashed (dashed-dotted) lines depict the corresponding employment-weighted average responses for a subset of industries with a high (low) average trade share.

responses of price and wage inflation and of output and employment growth are very similar to their corresponding unweighted median industry-level responses shown in Figure 10: In response to an adverse commodity price shock, producer price inflation increases sharply, while output growth—after rising initially—turns negative after several quarters; employment growth and wage inflation are also initially positive before sliding into a negative territory.

The differential response of producer prices across the two industry groups indicates that price inflation in low trade intensity industries is substantially more sensitive to fluctuations in commodity prices compared with their high trade intensity counterparts. At the two-quarter horizon, annualized inflation jumps a full percentage point in low trade intensity industries, while increasing only about 20 basis points in high trade intensity industries. This stark difference in the response of producer prices occurs despite the fact that the commodity price shocks causes output, employment, and wages to behave in a very similar manner in the two industry groupings.

It is once again instructive to focus on the cumulative effects of price inflation and output growth to gauge how differences in trade exposure across industries affect the sensitivity of producer prices to fluctuations in output induced by aggregate supply shocks. The differential dynamics of producer price inflation in response to a commodity price shock translate into substantial differences in the sensitivity of inflation to movements in output—at all horizons—between industries with low and high international trade exposure. At the two-year horizon, producer prices in low trade intensity industries are estimated to rise one percent for every one percent drop in industrial output; in high trade intensity industries, by contrast, producer prices are estimated to increase a mere 0.2 percent for the same-sized decline in output. As in the case of financial shocks, therefore, our estimates indicate that in industries with a low trade exposure, producer price inflation is significantly more sensitive to fluctuations in output induced by commodity price shocks compared with industries with a high trade exposure.

In summary, our FAVAR analysis implies that producer price inflation is three to four times more responsive to both aggregate demand and aggregate supply shocks in low trade intensity industries compared with their high trade intensity counterparts. Responses of wages, output, and employment, by contrast, are strikingly similar across the two industry groupings. These results are consistent with the notion that the Phillips curve is indeed much flatter in industries that are more exposed to international trade and are thus broadly consistent with our earlier findings, which show that the estimated flattening of the aggregate Phillips curves coincides to a substantial degree with the increased exposure of the U.S. economy to international trade.

5 Conclusion

In this paper, we examine the extent to which the response of inflation to fluctuations in economic activity has weakened over time. Furthermore, we analyze the role that globalization and rising trade shares can help account for these shifts. Our evidence points to a significant flattening of the Phillips curve that occurred in the 1990s. Although there is some evidence of a recent rise in the responsiveness of CPI inflation to changes in economic slack, it remains the case that both PPI and CPI inflation are substantially less responsive to fluctuations in economic activity today, relative to estimates that rely on the pre-1990 data. To a significant degree this reduced responsiveness of inflation to economic slack coincides with a rising U.S. trade share and increased globalization.

Industry-level data provide further evidence in favor of the notion that trade intensity attenuates the response of inflation to fluctuations in economic activity. Industry-level estimates of Phillips curve imply a substantially lower responsiveness of PPI inflation to output in industries with a high trade share, relative to those with a low trade share. We confirm these results by examining the response of industry-level PPI inflation and output to identified aggregate demand and supply shocks. This evidence implies that the inflation-output tradeoff is three to four times larger for low trade intensity industries compared with their high trade intensity counterparts. In this sense, increased international trade and globalization do indeed appear to help explain the observed flattening of the aggregate Phillips curve over the past several decades.

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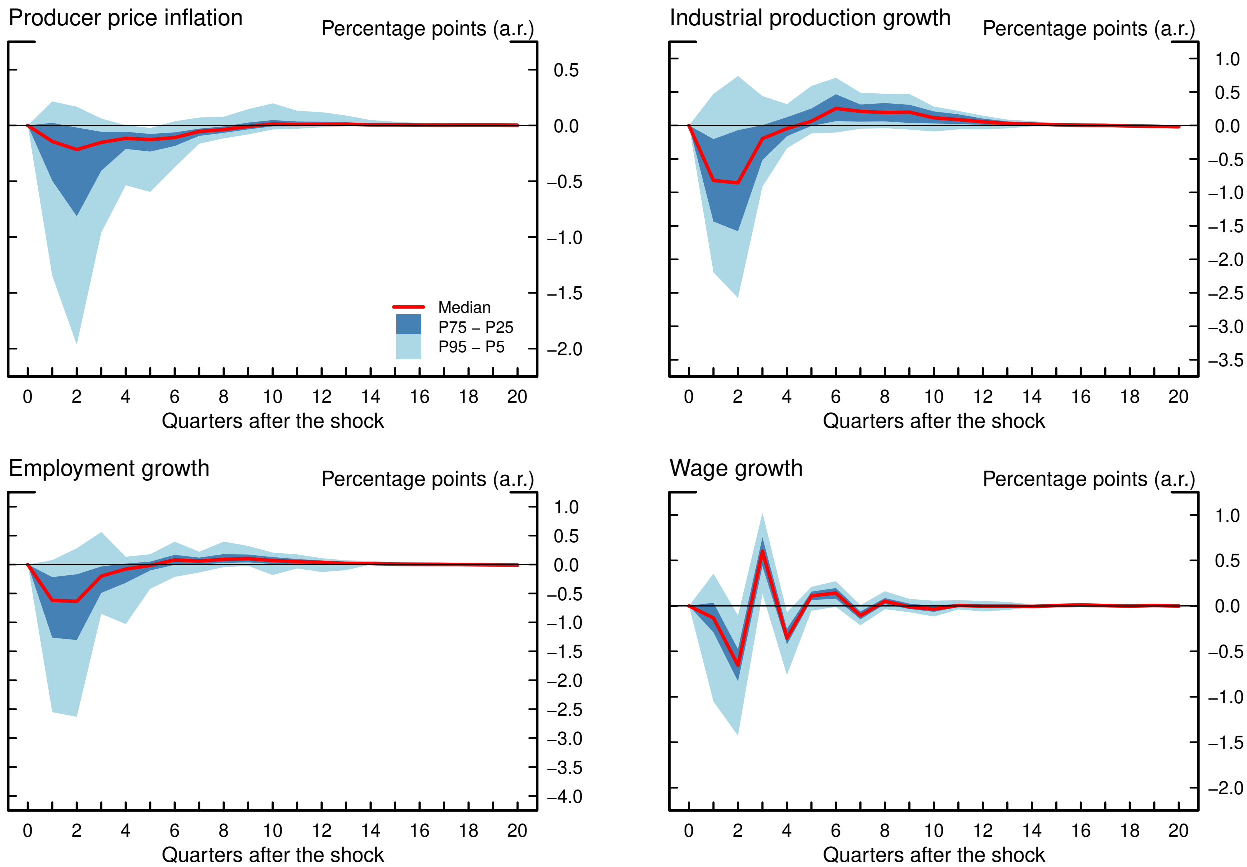
Appendix

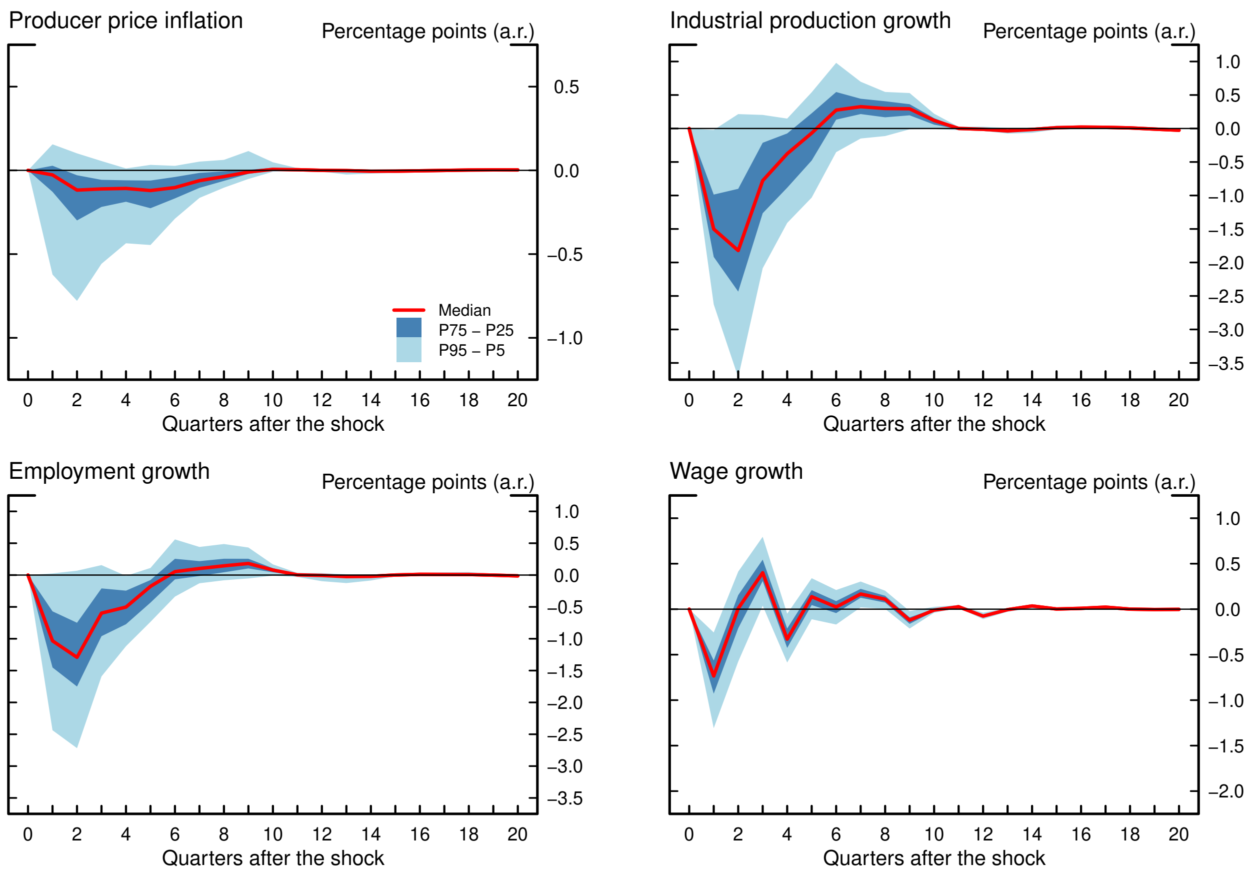
A Supplementary Results

Figure A-1: Implications of an Adverse Financial Shock
(Industries With a Low Trade Share)



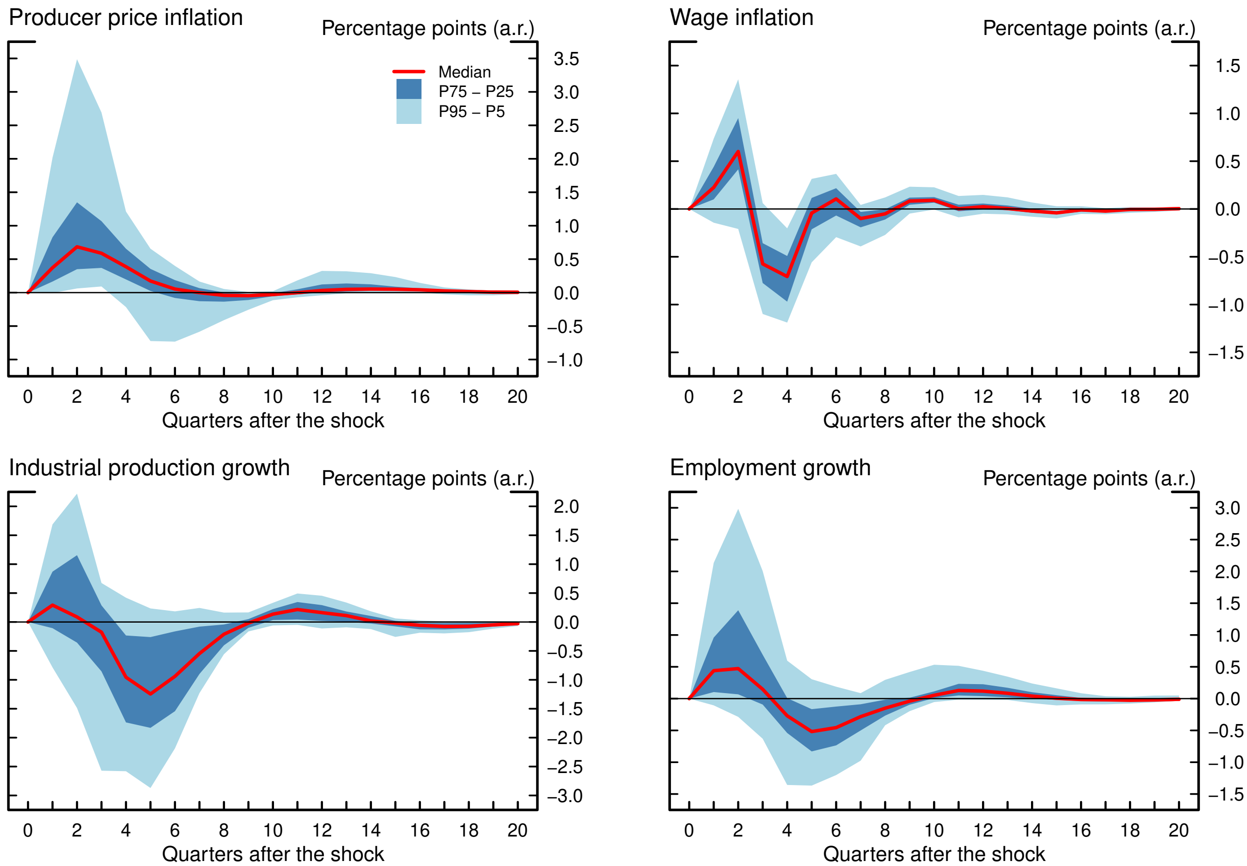
Note: The solid line in each panel depicts the median response of the specified variable to an adverse financial shock of one standard deviation across a subset of industries with a low average trade share; the shaded bands depict the corresponding $P75 - P25$ and $P95 - P5$ ranges.

Figure A-2: Implications of an Adverse Financial Shock
(Industries With a High Trade Share)



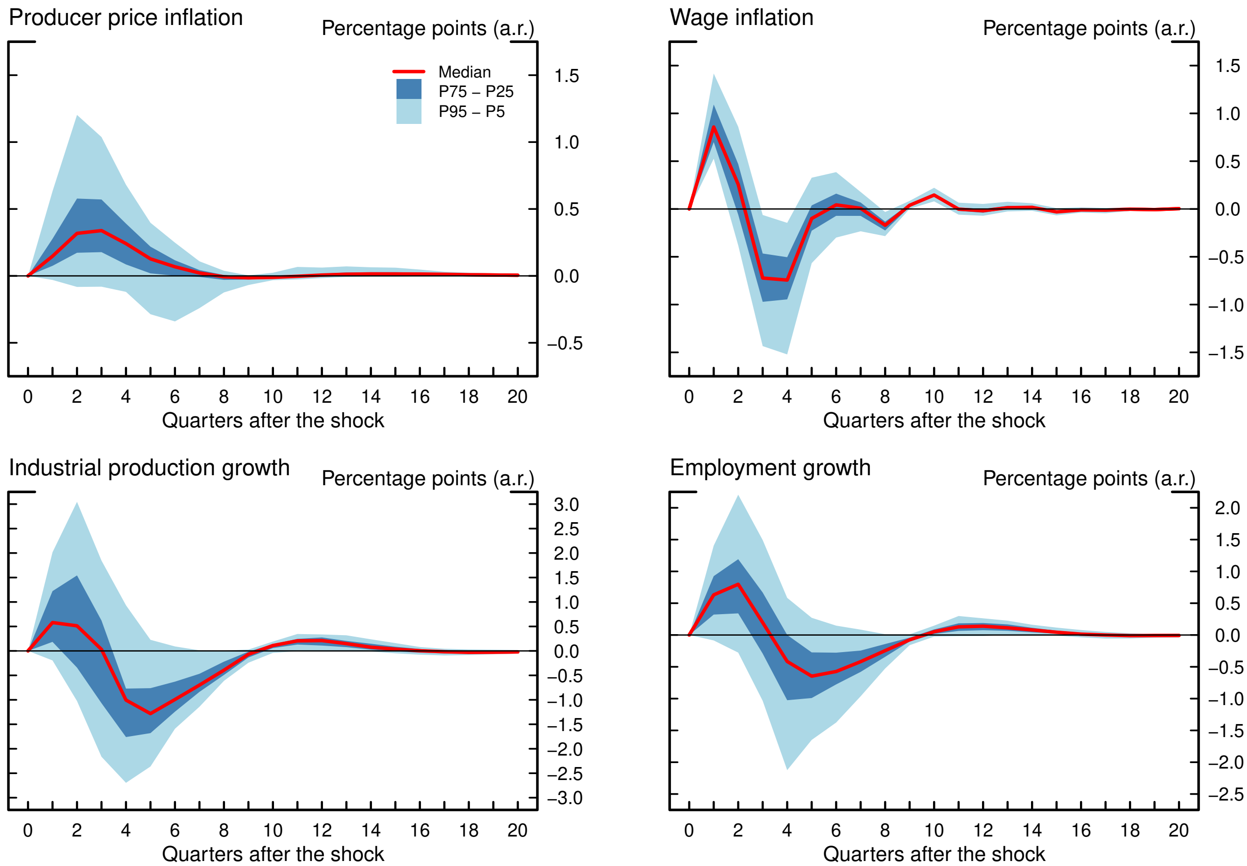
Note: The solid line in each panel depicts the median response of the specified variable to an adverse financial shock of one standard deviation across a subset of industries with a high average trade share; the shaded bands depict the corresponding $P75 - P25$ and $P95 - P5$ ranges.

Figure A-3: Implications of an Adverse Commodity Price Shock (Industries With a Low Trade Share)



Note: The solid line in each panel depicts the median response of the specified variable to an adverse commodity price shock of one standard deviation across a subset of industries with a low average trade share; the shaded bands depict the corresponding $P75 - P25$ and $P95 - P5$ ranges.

FIGURE A-4: Implications of an Adverse Commodity Price Shock
(Industries With a High Trade Share)



NOTE: The solid line in each panel depicts the median response of the specified variable to an adverse commodity price shock of one standard deviation across a subset of industries with a high average trade share; the shaded bands depict the corresponding $P75 - P25$ and $P95 - P5$ ranges.