EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Lukas Henkel

Sectoral output effects of monetary policy: do sticky prices matter?

No 2473 / October 2020

Abstract

This paper studies the role of sticky prices for the monetary transmission mechanism, using disaggregated industry-level data from 205 US industries. There is substantial heterogeneity in the output responses of industries to monetary policy surprises. I show that an industry's response to monetary policy surprises is systematically related to an industry's degree of price stickiness as measured by the average frequency of price adjustment. The size of the differential reaction is economically large and statistically significant. The results suggest that sticky prices play an important role in the transmission of monetary policy, consistent with New Keynesian macroeconomic models. This result is robust to the inclusion of further industry-level control variables.

JEL Classification: E31, E32

Keywords: sticky prices, monetary transmission mechanism

Non-technical Summary

The goal of this paper is to test the importance of sticky prices for the monetary transmission mechanism. The question through which channels monetary policy affects real economic activity, like output or employment, is a long-standing one in monetary economics. New Keynesian models, arguably the most popular class of models used by central banks to analyse economic developments, greatly emphasize the role of nominal rigidities, in particular of price stickiness, for the monetary transmission mechanism. Price stickiness describes the fact that prices do not immediately react to economic shocks, but adjust rather infrequently.

If sticky prices indeed play an important role in the monetary transmission mechanism, it should be the case that the output of industries with more sticky prices reacts more strongly to monetary disturbances, compared to industries with more flexible (i.e. less sticky) prices. This prediction is commonly made by New Keynesian models with multiple production sectors. The goal of this paper is to empirically test this prediction made by New Keynesian models using disaggregate data on US manufacturing industries, providing an important test of the assumptions underlying the New Keynesian approach.

In a first step, I estimate the dynamic output response of 205 US manufacturing industries to monetary policy shocks using a panel VAR framework. Sectoral industrial production data is obtained from the Board of Governors of the Federal Reserve System. For each industry, an index measuring the (real) industrial production at monthly frequency is available. Importantly, all industries belong to the manufacturing sector. I then use a panel VAR framework to estimate the dynamic output response of these 205 to monetary policy shocks over the time period from December 1988 to December 2007. Monetary policy shocks are identified here as surprises to financial market participants. The output reactions of different industries to a (common) contractionary monetary policy shock differ substantially. Two years after a one standard contractionary monetary policy shock some industries experience a drop in output as large as 2%, while other industries even increase output by 0.9% in reaction to the same shock, at the same horizon.

In a second step, I show that an industry's output response to monetary policy shocks is systematically related to the industry's degree of price stickiness. Price stickiness at the industry level is measured via the (monthly) frequency of price adjustment. A high frequency of price adjustment means that prices are very flexible, whereas a low frequency of price adjustment indicates very sticky prices. The frequency of price adjustment at the industry level is calculated using the microdata underlying the monthly US producer price index (PPI) using data from the years 2005 to 2011. I regress the industry-level output response to a contractionary monetary policy shock on the log of the frequency of price adjustment at the industry-level. Industries with a higher frequency of price adjustment (i.e. less sticky prices) experience a smaller drop in output than industries with a lower frequency frequency of price adjustment (i.e. more sticky prices) in reaction to the same contractionary monetary policy shock. This result is robust to the inclusion of various industry-level control variables, intended to capture alternative transmission channels of monetary policy.

Qualitatively, the results established in this paper are consistent with predictions of multisector New Keynesian models. Quantitatively, the results provide empirical support for the New Keynesian view that sticky prices indeed play an important quantitative role in the transmission of monetary policy to real economic activity. In summary, this paper provides support to the view that sticky prices indeed matter for the monetary transmission mechanism, as presumed by New Keynesian models.

1 Introduction

Do sticky prices matter for the monetary transmission mechanism? Although there is growing consensus that prices are fixed in the short run at the micro level, the macroeconomic implications of this micro-level price stickiness are heavily debated. On the one hand, New Keynesian sticky price models postulate that firms face costs of price adjustment, which causes prices to be sticky in response to real and nominal shocks and that it is this feature that gives rise to monetary non-neutrality. On the other hand, the observed price rigidity does not necessarily imply that nominal shocks have real effects. For example Caplin and Spulber (1987) and Golosov and Lucas (2007) present theoretical models in which prices are sticky and money is neutral or the response to nominal shocks is only very limited.

The goal of this paper is to empirically test whether sticky prices matter for the monetary transmission mechanism. If price stickiness plays an important role in the monetary transmission mechanism, the output of industries with a higher degree of price stickiness should react more strongly to monetary policy shocks than the output of industries with a lower degree of price stickiness. This paper investigates this testable implication of New Keynesian models using disaggrated US industrial production data.

The main finding of this paper is that there is a statistically significant association between an industry's output response to monetary policy shocks and the industry's degree of price stickiness, a finding that is new to the literature. The drop in output is estimated to be larger for sticky price industries (compared to flexible price industries) in response to a contractionary monetary policy shock. The size of this association is also economically significant. The cumulative drop in total industrial production is estimated at 0.38% two years after a one standard deviation contractionary monetary policy shock. For the most sticky price industries in the sample[1] the cumulative drop in output is estimated to be twice as large as the drop in total industrial production at the same horizon in response to the same monetary policy shock. At the same time, the cumulative drop in output is estimated at only half the size of the drop in total industrial production for the most flexible price industries in the sample[2] at the same horizon in response to the same monetary policy shock. Indeed, sticky price industries experience a larger change in output in response to monetary policy shocks, consistent with a New Keynesian price stickiness channel in the monetary transmission mechanism.

[1] Defined as industries at the 10th percentile of the in-sample distribution of the frequency of price adjustment.
[2] Defined as industries at the 90th percentile of the in-sample distribution of the frequency of price adjustment.

This conclusion is reached in several steps. First, I estimate the output responses of 205 manufacturing industries to monetary policy shocks. Monetary policy shocks are identified using the financial market based identification of Barakchian and Crowe (2013). Industry-level output responses to the identified monetary policy shocks are estimated in a Panel VAR framework. There is substantial heterogeneity in the output responses of industries to monetary policy shocks. The cumulative drop in total industrial production is 0.38% two years after an unexpected one standard deviation increase in the policy measure. For some industries the drop in output is as large as 2%, whereas other industries increase output by around 0.9% in response to the same shock. In a next step, this heterogeneity in output responses to monetary policy shocks is used to investigate the transmission channels of monetary policy to real economic activity.

The goal of this paper is to asses the role of price stickiness in the monetary transmission mechanism. Following the empirical literature on price rigidities (e.g. Bils and Klenow (2004) and Gorodnichenko and Weber (2016)), price stickiness is measured via the monthly frequency of price adjustment at the industry level. The frequency of price adjustment is calculated for the manufacturing industries in the sample using monthly PPI micro data over the period from 2005 to 2011.[3] The frequency of price adjustment differs greatly between industries. The most sticky price industries adjust only 4% of prices per month on average over the sample period. On the other hand, the most flexible price industries adjust 87% of prices per month. The median frequency of price adjustment of the industries in the sample is 19%.

In order to asses the association between an industry's output response to monetary policy shocks and the industries frequency of price adjustment, the cross-section of industry responses (at different horizons after the shock has happened) is regressed on the industry-level (log of the) frequency of price adjustment. More flexible prices are associated with a less strong drop in output in reaction to contractionary monetary policy shocks. A 10% increase in the frequency of price adjustment is associated with a 0.035 percentage point reduction in the cumulative output drop in response to the policy shock (2 years after the shock). Compared to the cumulative drop in total industrial production index, which is 0.38%, the size of this association is economically (and statistically) significant. A 10% increase in the frequency of price adjustment is associated with a reduction in the output drop in response to a contractionary policy shock that is as large as 10% of the average drop in output. Hence an increase in the frequency of price adjustment is

[3] I am grateful to Michael Weber for providing the industry-level frequency of price adjustment to me.

associated with a less strong reaction to monetary policy shocks, consistent with a New Keynesian price stickiness channel of monetary transmission.

In a next step several additional industry characteristics are added to the regression of the industry output responses to monetary policy shocks on the log of the frequency of price adjustment. Industries do not only differ along their frequency of price adjustment but also along other dimensions. Controlling for additional industry characteristics helps to disentangle the effect of price stickiness from other potentially confounding factors. The additional industry characteristics considered here include e.g. measures of external financial dependence or industry cyclicalty. When controlling for other industry characteristics, the association between the frequency of price adjustment and the strength of the reaction to monetary policy shocks becomes even larger, providing further support for a price stickiness channel in the monetary transmission mechanism.

The remainder of this introduction presents an overview over the related literature and a roadmap of the paper. The analysis in this paper is related to different strands of the literature on the monetary transmission mechanism. First, it is realted to a number of papers such as Peersman and Smets (2005), Ganley and Salmon (1997), Hayo and Uhlenbrock (2000) and Dedola and Lippi (2005) that examine the industry effects of monetary policy shocks. All these papers find considerable cross-industry heterogeneity in the output reaction to monetary policy shocks (identified from SVARs). While Ganley and Salmon (1997) and Hayo and Uhlenbrock (2000) focus on the UK and Germany, respectively, Dedola and Lippi (2005) and Peersman and Smets (2005) analyze cross-country differences in the monetary policy transmission mechanism as well. These papers find that the durability of industry output is a significant determinant of cross-industry heterogeneity in the output responses to monetary policy shocks, with durable goods producing industries reacting more strongly. In the US, Carlino and DeFina (1998) find substantial heterogeneity across regions in the response to monetary policy shocks. None of these papers has considered heterogeneity in price stickiness as explanatory variable in their analysis of cross-industry heterogeneity in responses to monetary policy shocks.

Gorodnichenko and Weber (2016) show that after monetary policy announcements the conditional volatility of stock market returns rises more for firms with stickier prices than for firms with more flexible prices. Their finding indicates that menu costs are an important factor causing nominal price rigidities, as presumed by New Keynesian models.

Hong, Klepacz, Pasten, and Schoenle (2020) follow a related approach as the paper at hand and use industry-level US PPI inflation rates and different micro pricing moments to study which price setting moments are most informative for monetary non-neutrality. Out of the eight different micro pricing moments they consider, they find that only frequency has an empirically robust relationship with monetary non-neutrality.

Furthermore, the findings of this paper speak to the literature on multi-sector New Keynesian models of the monetary transmission mechanism. A common finding in the literature on multi-sector New Keynesian models is that heterogeneity in the degree of price stickiness across sectors enhances monetary non-neutrality, e.g. Bouakez, Cardia, and Ruge-Marcia (2013) or Pasten, Schoenle, and Weber (2018b). In these types of models, industries with a higher degree of price stickiness (ceteris paribus) react more strongly to monetary policy shocks (see e.g. Bouakez, Cardia, and Ruge-Marcia (2013) and Ghassibe (2018)). This finding is not limited to models that use nominal price rigidities modeled as in Calvo (1983), but can also be extended to multi-sector menu cost models. For example in the calibrated multi-sector menu cost model of Nakamura and Steinsson (2010), the output of sectors with a lower frequency of price adjustment reacts more strongly to nominal demand shocks. The analysis at hand speaks to this literature by testing this testable implication of multi-sector models of the monetary transmission mechanism.

It should be noted that testing this prediction of multi-sector New Keynesian models speaks to New Keynesian models of the monetary transmission mechanism in general. New Keynesian models greatly emphasize the role of nominal rigidities, in particular price stickiness, for the monetary transmission mechanism and as the source of monetary non-neutrality policy (Galí (2015)). Hence the test whether price stickiness has a role in explaining differential industry reactions to monetary policy shocks is an important test of the New Keynesian paradigm.

The rest of the paper is organized as follows. Section 2 presents the data used in the analysis. Section 3 presents the response of (total) industrial production to monetary policy shocks. Section 4 presents the output responses of 205 manufacturing industries to monetary policy shocks. Section 5 presents the relationship between an industries output response and the frequency of price adjustment. In Section 6 presents this relation when controlling for additional industry characteristics. Section 7 presents various robustness checks. Section 8 summarizes the results and concludes.

2 Data

This Section presents the data used in the main part of the analysis. First, the sectoral industrial production data is described. Next, I describe how price stickiness is measured at the industry level. Lastly, the monetary policy shock series used in the analysis is presented.

2.1 Sectoral Industrial Production Data

Sectoral industrial production data is obtained from the Board of Governors of the Federal Reserve System. At the most disaggregated level, the Board of Governors publishes 213 monthly industrial production index series, measuring the monthly real output of the industries covered by these series. These series are the basis used to construct the commonly used (aggregate) monthly industrial production index for the US. The 213 series cover the whole manufacturing sector plus part of the mining and utilities sectors. Industries covered by the industrial production index are classified in the 2007 version of the North American Industrial Classification System (NAICS)[4]. All series are non-overlapping in terms of NAICS 6-digit industries, i.e. every NAICS 6-digit industry is contained in at most one industrial production series. The level of disaggregation used here is the finest level of disaggregation at which monthly industrial production data is published. The analysis here is confined to industries covered by the industrial production index due to a lack of (disaggregated) monthly output data for other sectors of the economy (like services). All series are seasonally adjusted.

The series used in the industrial production index cover the whole manufacturing sector (NAICS groups 31 - 33), plus those industries that have traditionally been considered to be manufacturing, namely NAICS 1133 (logging) and 5111 (newspaper publishing)), mining and oil extraction (NAICS groups 211-213) and electrical power generation and gas distribution (NAICS 2211 and 2212).

[4]NAICS is the North American Industry Classification System. The finest level of disaggregation available in this classification scheme is the 6-digit classification. NAICS is a hierarchical classification scheme, with the digit-length of the NAICS code indicating the level of disaggregation. For example, several NAICS 6-digit industries can share the same 5-digit industry code.

The Board of Governors does not publish a separate output series for every single NAICS 6-digit industry (which is the finest level of disaggregation in the NAICS classification system). Instead, some NAICS 6-digit industries are grouped together with other (similar) NAICS 6-digit industries that share the same 4- or 5-digit NAICS code.

This leads to the fact that 213 separate industrial production series are available from the Board of Governors[5]. I exclude eight series from the following analysis due to missing data on the frequency of price adjustment for these series. Hence in the following analysis, 205 monthly industrial production series are used.

2.2 Data on Price Stickiness

Price stickiness is measured by the (monthly) frequency of price adjustment (FPA) at the level of the industrial production series. This follows the standard approach in the empirical literature (e.g. Bils and Klenow (2004), Nakamura and Steinsson (2008) and Gorodnichenko and Weber (2016)) to measure the degree of price stickiness via the (monthly) frequency of price adjustment. A high frequency of price adjustment implies low observed price stickiness, and vice versa.

The frequency of price adjustment is calculated at the industry level from confidential micro-data underlying the US producer price index (PPI) from the Bureau of Labor Statistics (BLS)[6]. The PPI measures selling prices from the perspective of producers, in contrast to the CPI which measures prices from the perspective of consumers. For the analysis here, using the data underlying the PPI is desirable, as prices and output are measured at the same unit (i.e. the producer of the good).

The PPI tracks monthly prices of all goods-producing industries, such as manufacturing and mining. Every month, the BLS surveys the prices of around 100,000 individual items to construct the PPI. The PPI seeks to measure the entire marketed output of US producers (Goldberg and Hellerstein (2009)). The BLS uses a multi-stage sampling procedure to select the items included in the PPI. The sampling procedure is summarized here, based on information given in the BLS Handbook of Methods, chapter 14.[7] Similar summaries of the sampling procedure for the PPI used by the BLS can be found in e.g. Gorodnichenko and Weber (2016), Nakamura and Steinsson (2008), Pasten, Schoenle, and Weber (2018a) and Goldberg and Hellerstein (2009).

[5]There are 472 unique 6-digit NAICS industries in the manufacturing sector in the 2007 NAICS classification.

[6]I am grateful to Michael Weber for providing the data on the frequency of price adjustment at the industry level to me.

[7]Available under https://www.bls.gov/opub/hom/pdf/ppi-20111028.pdf.

In an initial step, the BLS selects the producers, so-called price-forming units, to be included in the PPI. Selection of price-forming units is stratified by industry and based on the following procedure. First, for a given industry, the BLS compiles a list of all establishments (in that industry), based on the information given in the Unemployment Insurance System[8]. In the next step, establishments are clustered into so-called price-forming units. Price-forming units are establishments belonging to the same company, within the same industry. This ensures that prices are collected at the level relevant for price setting, as several establishments owned by a single company may be operated as a cluster and constitute a profit-maximizing center. Finally, a sample of price-forming units is selected to be included in the PPI, with the probability of selection being proportional to its employment size[9].

After a price-forming unit has been selected (and agreed to participate) in the PPI survey, the BLS selects which items produced by the price-forming unit are included in the PPI. Selection of individual items is based on a probability sampling technique called dissaggregation. In the dissaggregation procedure, BLS field economists first combine individual items of a price-forming unit into categories, and assign sampling probabilities to each category proportional to the value of shipments within the reporting unit. Next, the selected categories are broken into additional detail in subsequent stages, until unique items are identified. If the same item is sold at more than one price, then the all price-determining characteristics — for example size and unit of shipments, freight type, type of buyer or color of the item — also must be selected on the basis of probability. This method for identifying the exact transaction terms and price-determining characteristics ensures that the same type of transaction is priced over time.

In line with this procedure, the PPI defines prices as "net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped under specified transaction terms on a specified day of the month". Taxes and fees collected on behalf of the (federal, state, or local) government are not included in the price. Sales and temporary reductions are reflected in collected prices in so far as they reduce the revenue generated by a specific item received by the producer.

The BLS collect prices from around 25,000 establishments for approximately 100,000 individual items on a monthly basis. Prices are collected by means of a survey that is e-mailed or faxed to participating establishments. An establishment will remain in the sample for seven years,

[8] Most employers are legally required to participate in the Unemployment Insurance System.

[9] Possibly within several strata defined by the BLS for a given industry

until a new sample is selected to account for changes in industry structure and changing product market conditions within the industry.

The prices of individual items (defined as above) reported in the PPI database are used to calculate the frequency of price adjustment (FPA) at the industry-level. The FPA at the industry level is calculated using the same method as Pasten, Schoenle, and Weber (2018a) and Gorodnichenko and Weber (2016). This method is described here.

First, the FPA is calculated for every single item in the data. The FPA at the item level is calculated as the ratio of the number of price changes to the number of sample months. To illustrate this, consider the following (hypothetical) example. Suppose an item is observed in the data for 5 months. The observed price path of this item is \$10 for two months and then \$15 for another three months. Here, one price change occurs during five months, hence the frequency of price adjustment is $1/5$ for this item. Price changes due to sales are uncommon in PPI data, but are excluded in the calculation of the FPA, following Pasten, Schoenle, and Weber (2018a) and Gorodnichenko and Weber (2016). To calculate the FPA at the industry-level, the item-based frequencies are aggregated to the industry level, giving equal weight to all products produced by this industry. The FPA of an industry is hence given as the average FPA of all items produced by this industry.

Industry-level frequencies are calculated at the NAICS 6-digit, 5-digit, 4-digit and 3-digit level. The industry-level frequencies of price adjustment are matched to the corresponding industrial production series.[10]

The PPI sample used to calculate frequency of price adjustment ranges from the years 2005 to 2011. The average monthly frequency of price adjustment across all industrial production series is 23.37%, implying an average price duration, $-1/ln(1-FPA)$, of 3.7 months. Substantial heterogeneity is present in the frequency across sectors, ranging from as low as 4.01% (for Semiconductor Machinery Manufacturing, NAICS 333295) to as high as 87.5 % (for Crude Petroleum and Natural Gas Extraction, NAICS 211111). Detailed summary statistics for the frequency of

[10] If an industrial production series consists of multiple NAICS 6-digit industries, but does not cover the whole (corresponding) NAICS 5-digit industry, the series is assigned the mean of the FPA of the included NAICS 6-digit industries (giving equal weight to all industries). Consider the following example. There are 4 different NAICS 6-digit industries included in a specific NAICS 5-digit industry. The Board of Governors reports an output series for the first NAICS 6-digit industry and a series reporting the combined output of the remaining three NAICS 6-digit industries. The first series, consisting of a single industry, is assigned the frequency of price adjustment of the corresponding NAICS 6-digit industry. The other series is assigned the average of the reported FPA of the three NAICS 6-digit industries included in the series. This method is used to calculate the FPA for 33 industrial production series.

price adjustment can be found in Table 8 in the Appendix. Figure 7 in the appendix shows a histogram of the distribution of the frequency of price adjustment (left Panel) and the distribution of the log of the frequency of price adjustment (right Panel). Around 50% of industries in the sample have a frequency of price adjustment between 15% and 25% per month (corresponding to an average duration between 6 and 3.5 months).

2.3 Monetary Policy Shocks

Identification of unanticipated, presumably exogenous shocks to monetary policy is a widely discussed topic in the macroeconomic literature. This paper does not propose a new identification scheme for monetary policy shocks, but uses an existing measure of monetary policy shocks from the literature, namely the one proposed by Barakchian and Crowe (2013). Monetary policy shocks in Barakchian and Crowe (2013) are identified as the (financial-market based) 'surprise' component of monetary policy actions, estimated using movements in Fed Funds futures contract prices on the day of monetary policy announcements following meetings of the Federal Open Market Committee (FOMC).

Here, I describe the identification of monetary policy shocks in Barakchian and Crowe (2013) in detail, following their exposition closely. Barakchian and Crowe (2013) identify monetary policy shocks using high-frequency data on Federal Funds futures contracts, financial derivatives whose payoff is calculated based on the effective federal funds rate. Federal Funds futures contracts have been traded since October 1988 (see e.g. Söderström (2001)). The price of a futures contract for month $m+h$ (i.e. at a horizon h from the current month m) is a bet on the monthly average effective Fed Funds rate in month $m+h$, here denoted by $\bar{r}^e_{m+h}$. As Barakchian and Crowe (2013) point out, the average effective Funds Rate might differ from the average target Fed Funds rate ($\bar{r}_{m+h}$, the policy rate set by the Fed) due to implementation errors on part of the Fed:

$$\bar{r}^e_{m+h} = \bar{r}_{m+h} + \epsilon_{m+h} \tag{1}$$

where ϵ_{m+h} is the average targeting error for month $m+h$. The futures rate on day d in month m with horizon h is then given by

$$f^h_d = E_d(\bar{r}^e_{m+h}) + \rho^h_d \tag{2}$$

where ρ_d^h is a possible risk premium. Under the assumption of an unchanged risk premium and no change in the expected average targeting error during subsequent calendar months ($h \geq 1$), the change in the expected target rate following a policy announcement on a day d of month m is given by

$$\Delta E_d \bar{r}_{m+h} = f_d^h - f_{d-1}^h \tag{3}$$

The change in the remainder of the current month (with length M days) is given by

$$\Delta E_d \bar{r}_m = \frac{M}{M-d}(f_d^0 - f_{d-1}^0) \tag{4}$$

so the change in the expected target rate is proportional to the (scaled) jump in the futures rate around the policy announcement.

Barakchian and Crowe (2013) calculate the change in the futures rate by comparing the end of day price on the day following the (last) day of an FOMC meeting with that on the meeting day for meetings occurring before February 1994. After February 1994, the change in the futures rate is calculated by comparing the end of day price on the meeting day with the end of day price on the day before the meeting. The analysis is confined to days with FOMC meetings, inter-meeting changes in the target rate are not considered.

The change in the futures rate is calculated for 6 different maturities, starting with the future contract maturing in the current month ($h = 0$), up to the future contract maturing five months after the meeting ($h = 5$). The monetary policy shock measure is then defined as the first principal component of the jump in the futures rate of all 6 maturities. This approach has several advantages over just considering a single maturity. First, this approach minimizes the effect of noise in a specific maturity. Second, as policy decisions are persistent over time, a policy change in the current period will also affect the futures rate several periods ahead. Hence taking into account longer maturities might reveal information of the persistence of the shock. This is important as persistent shocks should have a greater impact on economic activity. It should be noted that financial market based identification schemes of monetary policy shocks, like the one used here, assume that financial market participants beliefs about the Fed's information set prior to the announcement of monetary policy actions are correct, i.e. that unexpected changes[11] in the federal funds rate are indeed due to monetary policy shocks, and not due to superior information

[11] Unexpected from the viewpoint of financial market participants

of the Fed. To assess this assumption, Barakchian and Crowe (2013) regress their monetary policy shock measure on the difference between the Fed's Greenbook forecasts and high-quality private sector (Blue Chip) forecasts for the 17 variables used in Romer and Romer (2004), where this difference in forecasts is used as a proxy for the Fed's internal information. They find little evidence of superior information of the Fed compared to financial market participants[12]. This suggests that the shock measure used here should be relatively uncorrelated with the Fed's exclusive information, and superior information on the side of the Fed should therefore not be a significant problem. In Section 7, I consider a different identification scheme of monetary policy shocks that explicitly controls for the Fed's information set in the identification of monetary policy shocks and find very similar results as in the baseline analysis using the shock measure of Barakchian and Crowe (2013).

The shock series is available from December 1988 onwards at monthly frequency. By construction, the policy shock has mean zero and a standard deviation of one. A detailed overview over the identification of monetary policy shocks can be found in Ramey (2016). The data used here can be downloaded from the website of Valerie Ramey, available at `http://econweb.ucsd.edu/~vramey/research.html#data`. A graph depicting the time series of the shock measure can be found in the Appendix in Figure 6.

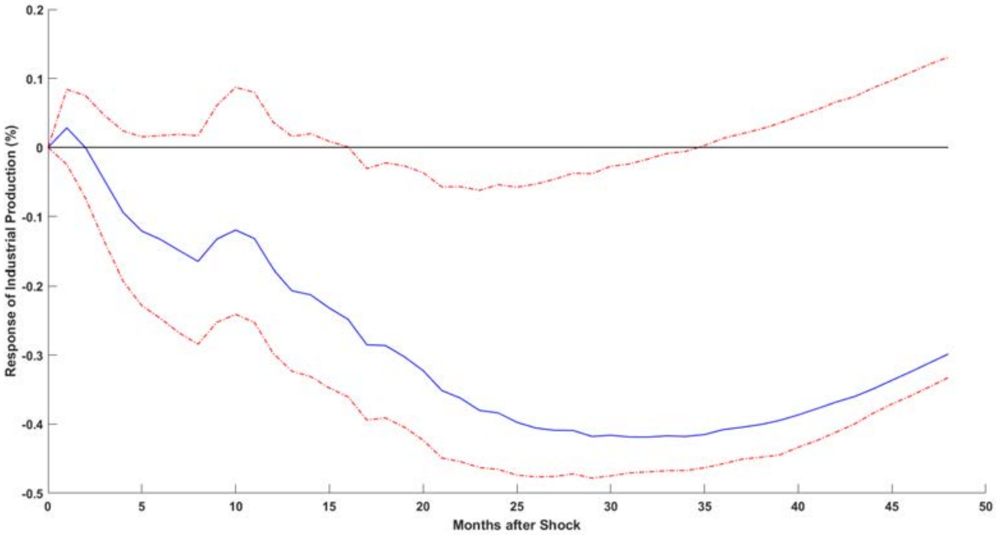
3 Aggregate Effects of Monetary Policy Shocks

Before turning to the reaction of different industries to monetary policy shocks, I estimate the reaction of (aggregate) industrial production (and other aggregate variables) to monetary policy shocks in this Section. To estimate the dynamic effects of the identified policy shocks on aggregate variables, I include the cumulated identified shock measure in a VAR. This approach is similar to Romer and Romer (2004) and common in the empirical literature on monetary policy transmission (Ramey (2016)). The specification of the VAR follows Coibion (2012) and includes the same set of variables used in Coibion (2012). The variables included are Industrial Production (in logs), the unemployment rate, the CPI (in logs), a commodity price index[13] (in logs) (all seasonally adjusted) and the cumulated shock series. The VAR is estimated at monthly frequency from December 1988 to December 2007.[14] The VAR includes 12 lags and a constant.

[12] The joint hypothesis of zero coefficients on all 17 variables cannot be rejected at the 10% level.
[13] Taken from Valerie Rameys website described above.
[14] I end the sample in December 2007 to abstract from issues related to the Zero Lower Bound.

Following the literature on monetary policy shocks in structural VARs, the recursive identification scheme of Christiano, Eichenbaum, and Evans (1999) is employed. Monetary policy is assumed to respond to, but not affect, the other variables contemporaneously. The specification used here employs the measure of policy shocks of Barakchian and Crowe (2013), whereas Christiano, Eichenbaum, and Evans (1999) use the actual funds rate. Since standard VARs enter the federal funds rate in levels, the shock series is cumulated to produce a comparable series. The same estimation procedure (with a different measure of policy shocks) is used in e.g. Romer and Romer (2004) or Coibion (2012). Similar specifications are commonly used in the literature (see Ramey (2016) for a detailed review). It should be noted that the recursiveness assumption is not necessary for identification of monetary policy shocks in the analysis at hand, as an identified shock series is used. In order to be comparable with the previous literature, in the baseline analysis the recursiveness assumption is used. The recursiveness assumption is relaxed in Section 7.

Figure 1: Response of Industrial Production to a Contractionary Monetary Policy Shock



Structural VAR (Monthly data, 5 endogenous variables, 12 lags). Variables ordered as industrial production (in logs), unemployment rate, consumer price index (in logs), commodity price index (in logs) (all seasonally adjusted) and the cumulated shock measure of Barakchian and Crowe (2013). The graph shows response of industrial production to a one standard deviation increase in the policy measure. Structural shocks obtained via Cholesky decomposition. Bootstrapped 90% Confidence Intervals based on 5000 Bootstrap Replications are shown in red.

Figure 1 shows the (cumulative) response of the aggregate industrial production index to a one standard deviation increase in the policy measure (in percent). After a one standard deviation increase in the policy measure, industrial production drops by around 0.38% 2 years after the shock has occurred. Qualitatively, the sign and the speed of the reaction are in line with other estimates found in the literature, e.g. Coibion (2012), Romer and Romer (2004) and Ramey (2016). The timing of the response is very similar to Barakchian and Crowe (2013), who use a different specification for their VAR. The size of the response is slightly larger than the estimated response in Barakchian and Crowe (2013) (whose specification implies a drop in output of around 0.3% 2 years after a one standard deviation contractionary shock). The size of the reaction is also comparable to other studies that use financial market based measures of monetary policy shocks. For example, Gertler and Karadi (2015) report a drop in industrial production of around 0.4% two years after a one standard deviation increase in their policy instrument. Also the timing of the response in Gertler and Karadi (2015) is very similar to the results reported here.

As the main focus of this of this study is the output response of different industries, the reactions of the other variables are relegated to Figure 8 in the Appendix.

4 The Industry Effects of Monetary Policy Shocks

This Section describes the output responses of the 205 industries to the identified monetary policy shocks. First, the econometric specification is discussed. Then, the results of the estimation are presented.

4.1 Econometric Specification

To estimate the effect of monetary policy shocks on the output of a particular industry i, the (log) output (seasonally adjusted) of industry i is added to the VAR described in the Section 3 as additional (sixth) variable.

Several additional identifying restrictions are imposed on the VAR, compared to the VAR in Section 3. The purpose of these restrictions is to ensure that the sequence of monetary policy shocks is the same for all industries i.

Let $Y_{t,i} = [IP_t, UNEMP_t, CPI_t, PCOM_t, CSHOCK_t, OUT_{t,i}]'$ denote the variables included in the VAR for industry i. The first five variables are the same as described in the previous Section and $OUT_{i,t}$ denotes the log of the industrial production index of industry i.

Denote the reduced-form VAR for industry i as[15]

$$Y_{t,i} = \sum_{p=1}^{P} \Phi_{p,i} Y_{t-p,i} + e_{t,i} \tag{5}$$

where $\Phi_{p,i}$ are the reduced-form VAR coefficients (with $P = 12$ in the specification used here) and $e_{t,i}$ denoting the mean zero reduced-form VAR residuals with variance-covariance matrix $E(e_{t,i}e'_{t,i}) = \Omega_i$.

In order to ensure that the sequence of (aggregate) shocks is the same for each industry i, several restrictions are imposed.

Assume that the structural form of the model for every industry i is given by

$$A_i(L)Y_{t,i} = v_{t,i} \tag{6}$$

where $A_i(L) = A_{0,i} - A_{1,i}L - \ldots - A_{P,i}L^P$ is a (invertible) lag polynomial of order P and L denotes the lag operator. The mutually uncorrelated structural innovations are denoted by $v_{t,i}$ with diagonal variance-covariance matrix Σ_i.

[15] The constant c is omitted here, i.e. the data is demeaned.

The goal of the following restrictions is to identify the reaction to the fifth element of the vector of structural shocks $v_{t,i}$, which is the innovation to the policy measure. Other structural shocks ordered before the policy variable are left unspecified (but common to all industries).

The relation between the structural parameters and the reduced-form coefficients is hence given by:

$$\Phi_{p,i} = A_{0,i}^{-1} A_{p,i} \tag{7}$$

$$\Omega_i = A_{0,i}^{-1} \Sigma_i (A_{0,i}^{-1})^T \tag{8}$$

In line with the recursiveness assumption made in the previous section, the matrix $A_{0,i}$ is assumed to be lower triangular with an additional zero restriction:

$$A_{0,i} = \begin{bmatrix} * & 0 & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & * & 0 & 0 \\ * & * & * & * & * & 0 \\ * & * & * & * & 0 & * \end{bmatrix} \tag{9}$$

where $*$ denotes an unrestricted coefficient. In economic terms, these restrictions imply the same recursiveness assumption that was invoked in the preceding section: Monetary policy shocks (ordered fifth) have no contemporaneous impact on all other variables in the system, including the output of industry i. The additional zero in the fifth column in the last row of matrix $A_{0,i}$ ensures that policy shocks have no contemporaneous impact on the output of industry i.

Additionally, the following restrictions are imposed on the structural VAR parameters for $p \neq 0$:

$$A_{p,i} = \begin{bmatrix} * & * & * & * & * & 0 \\ * & * & * & * & * & 0 \\ * & * & * & * & * & 0 \\ * & * & * & * & * & 0 \\ * & * & * & * & * & 0 \\ * & * & * & * & * & * \end{bmatrix} \tag{10}$$

Under these restrictions, the reduced-form parameter matrices $\Phi_{p,i}$ have zeros in the same place as the structural VAR parameter matrices $A_{p,i}$, the system has a block recursive structure. First, an aggregate block, containing the five aggregate variables, whose dynamics are the same for every industry i, and the same as the VAR described in Section 3. Second, an industry-specific block, whose coefficients are different for every industry i, which contains the output of industry i as only variable. It should be noted that these restrictions imply that sector-specific movements in industry i's output are constrained to affect the variables in the common subsystem (the aggregate variables) in proportion to the sector's share of total industrial production[16].

Imposing the structural restrictions described here ensures that the sequence of monetary policy shocks (and of the other, unspecified, common shocks) is the same for all industries i, and equal to the sequence of policy shocks in the estimation without industry i. Similar restrictions are imposed in Davis and Haltiwanger (2001), who refer to this set-up as "near-VAR". In fact, the whole system can be described as a restricted panel VAR, with a common block of macroeconomic variables and an industry-specific block (which here contains a single variable, industry i's output). One appealing feature of this estimation is that it allows sectoral responses to monetary policy shocks to vary freely, while keeping the same sequence of policy shocks and dynamics of aggregate variables for every industry i.

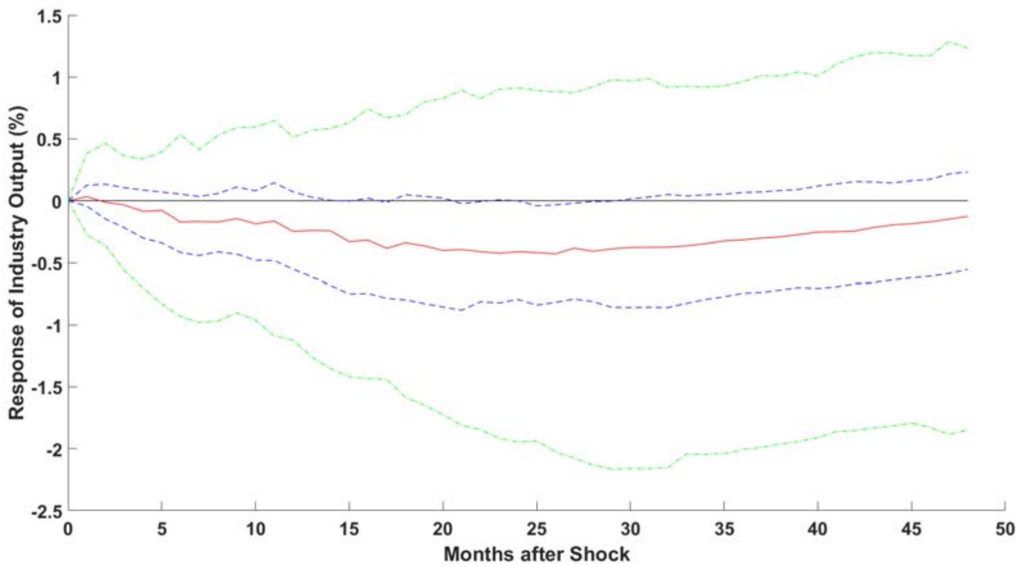
4.2 Results

The panel VAR described in Section 4.1 is estimated at monthly frequency using data from the period of December 1988 to December 2007. The VAR includes 12 lags and a constant, similar to the specification of the aggregate VAR described in Section 3.

[16] i.e. the feedback of industry i's output, $OUT_{t,i}$, on total industrial production IP_t and the other aggregate variables is not explicitly estimated, but the coefficients on (lagged) values of $OUT_{t,i}$ for the aggregate variables are constrained to be zero. However, movements in the output of industry i still have an effect on the aggregate system, due to the fact that total industrial production IP_t is a (weighted) sum of the output of all industries i.

Figure 2 shows the distribution of the dynamic output responses of the 205 industries to a one standard deviation contractionary monetary policy shock. The red line shows the median of the (cross-sectional) output responses (in percent) of the 205 industries at each horizon after the shock. The blue lines show the 25th and 75th percentile of the distribution of responses at each horizon after the shock, respectively. The green lines show the fifth and 95th percentile of the distribution of responses at each horizon.

Figure 2: Industry Responses to a Contractionary Monetary Policy Shock



This Figure shows the distribution of output responses of the 205 different industries to a one standard deviation contractionary policy shock identified as in Barakchian and Crowe (2013). Structural shocks are identified via Cholesky decomposition. Policy shocks and aggregate dynamics are common across industries. The red line shows the median response of all industries at each horizon. The blue lines show the 25th and 75th percentile of the distribution of the industries output responses at each horizon. The green lines show the fifth and 95th percentile of the distribution of the industries output responses at each horizon.

The median response of industries (red) tracks the response of aggregate industrial production well: 2 years after the shock has happened, the median industries output has fallen by around 0.4%. However, there is substantial heterogeneity present in the industries output responses. The interquartile range of responses is about 0.9% 2 years after the shock[17].

For some industries the fall in output is as large as 2% two years after the shock, i.e. around 5 times as large as the drop in total output. On the other hand, around 25% of industries even experience an increase in output in response to a contractionary policy shock. The fact that a substantial share of industries increase their output in response to contractionary monetary policy shocks deserves mentioning. In the multi-sector New Keynesian models of Ghassibe (2018) and Bouakez, Cardia, and Ruge-Marcia (2013), sectoral output responses are all negative in response to contractionary monetary shocks. In an extension of his model, Ghassibe (2018) shows that positive output reactions to a contractionary policy shock are only possible under an elasticity of substitution between sectors that is greater than one. The fact that a non-negligible share of sectors increases output after a contractionary policy shock is hence not consistent with the most basic versions of multi-sector New Keynesian models. In the multi-sector menu cost model of Nakamura and Steinsson (2010), several industries experience a drop in output in response a positive nominal demand shock[18], which is consistent with the empirical reactions presented here.

This result shows that there is indeed substantial heterogeneity in the output responses of industries to monetary policy shocks. A natural question to ask is which industry characteristics determine these differential reactions. The following Section investigates the role of heterogeneity in price stickiness across industries in determining these differential reactions.

[17] The difference between the 25 percentile and the 75 percentile of responses, which corresponds to the distance between the blue lines in Figure 2.

[18] which is the equivalent of monetary policy shocks in their model

5 The Role of Price Stickiness in Explaining Industry Output Reactions to Monetary Policy Shocks

The building blocks of New Keynesian Macroeconomics imply that the observed heterogeneity in the output responses to monetary policy shocks across industries should be systematically related to the degree of price stickiness of these industries. Industries with a higher degree of price stickiness should systematically react more strongly to monetary policy shocks (ceteris paribus). This prediction is made by various multi-sector New Keynesian models, for example Bouakez, Cardia, and Ruge-Marcia (2013) and Ghassibe (2018), but can also arise from multi-sector menu cost models like for example Nakamura and Steinsson (2010). Testing this prediction does not only speak to multi-sector New Keynesian models, but more generally to New Keynesian models of the monetary transmission mechanism. New Keynesian models greatly emphasize the role of nominal rigidities, in particular price stickiness, for the monetary transmission mechanism and the real effects of monetary policy (Galí (2015)). Hence the test whether price stickiness has a role in explaining differential industry reactions is an important test of the New Keynesian paradigm. This Section asses whether this proposed "price stickiness channel" is supported by the data.

To asses the correlation between price stickiness and the strength of the response to monetary policy shocks, I run the following regression:

$$IRF_i^h = \alpha^h + \beta^h log(FPA_i) + e_i^h \tag{11}$$

where IRF_i^h is the output response of industry i to an unexpected one standard deviation increase in the policy measure h months after the shock (measured in percent) and FPA_i is the monthly frequency of price adjustment of industry i. The frequency of price adjustment enters in logs rather than in levels to estimate the (semi) elasticity of the frequency of price adjustment.[19]

Note that a higher frequency of price adjustment means that prices are *less* sticky. The results of this regression for different horizons (18, 24 and 30 months) after the monetary policy shock can be found in Table 1. I focus on these horizons to be comparable with the previous literature on sectoral differences in the monetary policy transmission mechanism, e.g. Dedola and Lippi

[19] All results are robust to using the frequency of price adjustment in levels rather than logs as independent variable in the regression. The choice of using FPA in logs rather than levels is also motivated by the fact that, as can bee seen in Figure 8 in the Appendix, the distribution of the frequency of price adjustment is very skewed to the right, whereas the distribution of the logged frequency of price adjustment is more symmetrical.

(2005), and as the peak response of aggregate industrial production is reached between these horizons. Table 1 also reports the reaction of the (total) industrial production index h months after the shock.

It should be noted that the coefficient β^h here should not be interpreted as a causal effect, as price stickiness is not randomly assigned. β^h could only be interpreted as a causal effect if one assumes that there are no other factors that affect both, an industries reaction to monetary policy shocks, and this industries degree of price stickiness. In Section 6 I investigate how the estimated coefficient on the frequency of price adjustment changes once additional industry characteristics are added to the regression.

Table 1: Price Stickiness and Monetary Policy Responses

	(1) $h = 18$ Months	(2) $h = 24$ Months	(3) $h = 30$ Months
Log(FPA)	0.223	0.341**	0.339**
	(0.143)	(0.147)	(0.136)
Observations	205	205	205
R-squared	0.015	0.031	0.034
$I\bar{R}F^h$	-0.286	-0.383	-0.416

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports the coefficient on log(FPA) estimated in Equation 11 at different horizons h. The regression also includes a constant (not reported). $I\bar{R}F^h$ denotes the response of the (total) industrial production index h months after an unexpected one standard deviation increase in the policy measure. Robust Standard Errors are reported in Parenthesis.

The scatter plot underlying the regression for $h = 24$ can be found in the Appendix in Figure 9. For the horizons $h = 24$ and $h = 30$ months after the monetary policy shock, there is a statistically significant association between the strength of the response to policy shocks and the degree of price stickiness.

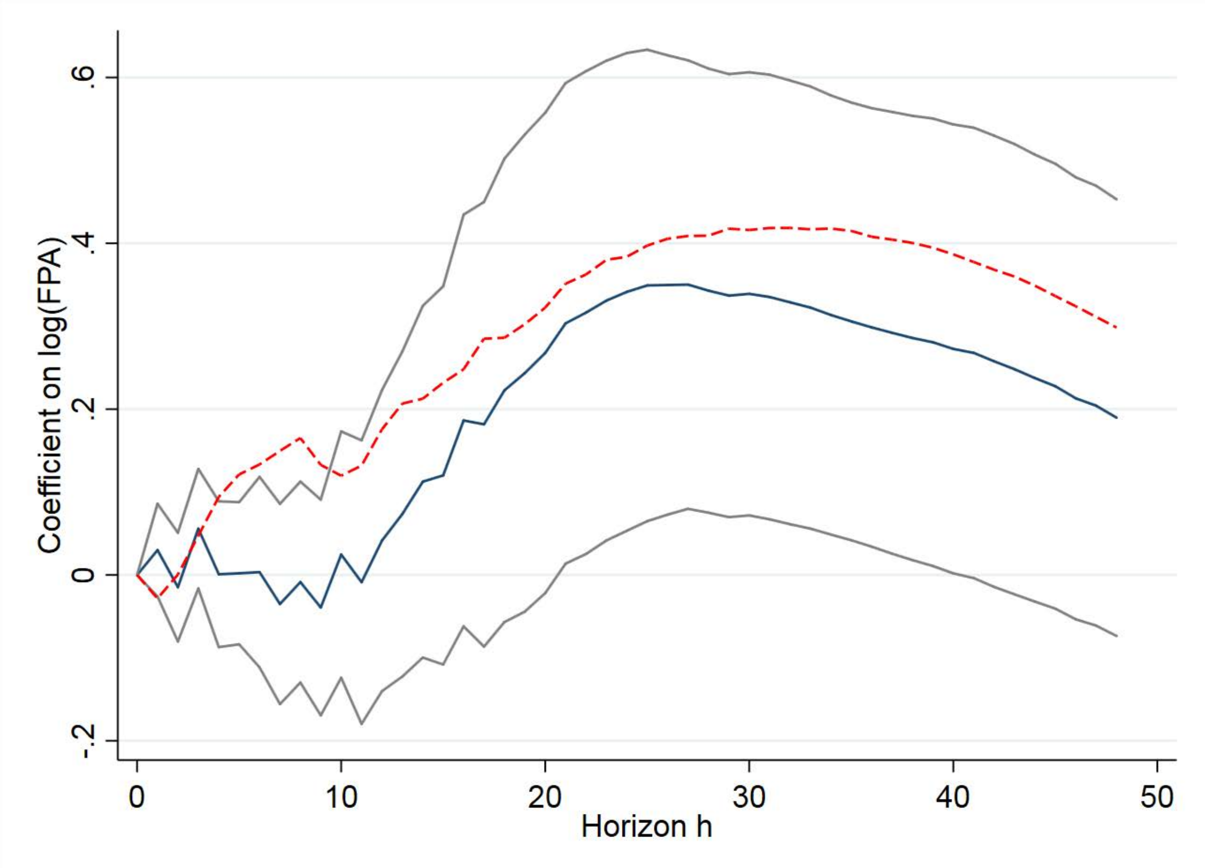
Qualitatively, the sign of the coefficient on the FPA is consistent with the predictions made by New Keynesian models. In response to the monetary policy shock, there is a drop in (total) industrial production (e.g. by 0.38% for $h = 24$ months). The positive sign on the regression coefficient means that, on average, industries with a higher frequency of price adjustment, i.e. more flexible prices, experience a *less* negative drop in output. This reaction is qualitatively in line with the prediction of (Multi-Sector) New Keynesian models: Industries with more flexible prices should react less strongly to monetary policy surprises. The positive sign on the coefficient shows that this is indeed the case: The magnitude of the reaction to policy shocks is lower for flexible price industries.

Quantitatively, the size of the coefficient is also economically significant. Consider the horizon of $h = 24$ months after the policy shock. A 10% increase in the frequency of price adjustment is associated with a 0.034 percentage point increase in the cumulative output response to the shock. Compared to the drop in the (total) industrial production index at the same horizon, which is 0.38, the size of this effect is economically meaningful: a 10% increase in the frequency of price adjustment leads to a less negative output response to the policy shock that is (approximately) as large as 10% of the total drop in output. The implied differential reaction between the most sticky price industries and the most flexible price industries is large. The tenth percentile of the in-sample frequency of price adjustment is given by 11.52 (meaning that on average 11.52% of prices are changed per month), implying a log(FPA) of 2.44. The 90th percentile of the in-sample frequency of price adjustment is given by 41.68, implying a log(FPA) of 3.73. The regression coefficient for the horizon of $h = 24$ months implies that the drop in output is $0.341 \times (3.73 - 2.44) = 0.44$ percentage points larger for industries at the tenth percentile of the in-sample frequency of price adjustment compared to industries at the 90th percentile of the in-sample frequency of price adjustment. Compared to the drop in total industrial production, which is 0.38 percentage points at the same horizon, this implied differential reaction is sizable.

The relative size of the effect is similar for the horizon of $h = 30$ months. For the horizon of $h = 18$ months, the sign and relative size of the coefficient are comparable to the other two horizons considered, but the coefficient is (marginally) insignificant (the p-value based on robust standard errors is $p = 0.12$).

Figure 3 shows the coefficient on log(FPA) estimated from Equation 11 for all horizons from $h = 0$ up to $h = 48$. Additionally, Figure 3 shows the inverted impulse-response function of total industrial production (i.e. the IRF is multiplied with (-1)). This Figure shows that for the first year after the shock there is no differential reaction between sticky and flexible price industries. However, when total industrial production starts to fall (around 1 year after the shock), the drop is stronger for sticky price industries than it is for flexible price industries. In fact, the coefficient on log(FPA) moves very much in parallel with the IRF of total industrial production (starting from $h = 12$ months after the shock), differences between sticky and flexible price industries coincide with the drop in aggregate output and do not seem to be driven by differences in the speed of the reaction.

Figure 3: Regression Coefficient on log(FPA) for different Horizons h



This Figure shows the time series of the estimated coefficient on log(FPA) from Equation 11 for all horizons from $h = 0$ up to $h = 48$ months after a contractionary policy shock. The blue line shows the estimated coefficient on log(FPA) at each horizon h. The gray lines are 95% confidence bands of the coefficient based on robust standard errors. The red, dashed line shows the inverted reaction of total Industrial Production in response to the policy shock in percent (i.e. the IRF is multiplied with (-1)).

6 Adding Further Industry Characteristics

The analysis so far has focused on differences in the frequency of price adjustment as source of heterogeneity in output responses between industries. However, the frequency of price adjustment is not the only (potential) factor determining an industries reaction to monetary policy shocks. For example, more cyclical industries exhibit a higher frequency of price adjustment (Klenow and Malin (2010)). At the same time, cyclical industries might exhibit a larger drop in output following a contractionary monetary policy shock, as they react more strongly to swings in economic activity. Not controlling for the cyclicality of an industry could hence lead to omitted variable bias in the estimated relationship between the frequency of price adjustment and the reaction to monetary policy shocks[20].

The goal of this Section is to assess to what extent the result established in the previous Section is affected by other (so far omitted) industry-level characteristics. To asses this further industry-level characteristics are added as additional control variables to Regression 11. The goal of this approach is to disentangle the role of the frequency of price adjustment from other potentially confounding factors in the monetary transmission mechanism. Regression 11 is hence changed to:

$$IRF_i^h = \alpha^h + \beta^h log(FPA_i) + \gamma^h X_i + e_i^h \tag{12}$$

where X_i denotes the additional industry-level control variables that will be added in this Section. Additional industry-level control variables X_i are added to the regression in order to test the robustness of the main result established in the Section 5. It should be noted that the goal of this analysis is not to explicitly test for the importance of other industry characteristics for the transmission of monetary policy, like e.g. the analysis of Peersman and Smets (2005) or Dedola and Lippi (2005). Hence the sign and size of the coefficients on the other industry-level control variables considered in this Section are not discussed in detail.

Before presenting the results of this exercise, I present an overview over the additional control variables included in Equation 12. The inclusion of the control variables is motivated either by the fact that an explicit link between the control variable and the frequency of price adjustment has been suggested, or by the fact that the variable has been found to be a significant determinant of industry-level responses to monetary policy shocks in the previous literature[21].

The full list of additional control variables is reported in Table 2. Whenever possible, variables are calculated as industry averages over the same time period that is used in Section 3 and 4. Summary statistics for the variables can be found in the Appendix in Table 9. Additional details on the calculation of the variables can be found in Section A in the Appendix.

The data sources used to calculate the additional control variables are the NBER-CES manufacturing database (denoted by NBER-CES in Table 2), the Compustat North America Fundamentals Annual database (denoted by Compustat in Table 2), the industrial production data

[20] In this specific example, failing to control for industry cyclicality should attenuate the coefficient on FPA towards zero.

[21] Even if an additional control variable should be orthogonal to the frequency of price adjustment, but influences an industries reaction to monetary policy shocks, the inclusion of this control variable will help to obtain more precise estimates of the effect of the frequency of price adjustment.

Table 2: Additional Control Variables and Data Sources

Variable	Source & Time Period	Frequency
Inventory over Sales	NBER-CES: 1988 - 2007	Yearly
Labor Cost over Sales	NBER-CES: 1988 - 2007	Yearly
Capital Intensity	NBER-CES: 1988 - 2007	Yearly
Average Firm Size (Number of Employees)	Economic Census 2007	Yearly
Interest Rate Burden	Compustat: 1988 - 2007	Yearly
Leverage Ratio	Compustat: 1988 - 2007	Yearly
Short-Term Debt Ratio	Compustat: 1988 - 2007	Yearly
Standard Dev. of Output Growth	Ind. Prod. Data: 1988 - 2007	Monthly
Cyclicality	Ind. Prod. Data: 1988 - 2007	Monthly
Durable Goods Dummy	BLS	Fixed

This Table presents an overview of the additional industry-level control variables considered in this Section.

form the Fed Board of Governors (described in Section 2, denoted by Ind. Prod. Data in Table 2) and the Durable Goods Producer definition of the Bureau of Labor Statistics (denoted by BLS in Table 2). In the following, the variables presented in Table 2 are explained in detail.

Inventory over Sales & Labor Cost over Sales: Industry-level differences in the reaction to monetary policy shocks might be driven by industry-level differences in the dependence on external funding (following Bernanke, Gertler, and Gilchrist (1999)). At the same time, Balleer, Hristov, and Menno (2017) document a link between financial constraints and the frequency of price adjustment at the firm level (using German survey data). To control for this potential link of external financial dependence and the frequency of price adjustment, the external financial dependence of an industry is added as additional control variable. Following Raddatz (2006), two measures of external financial dependence are calculated: The industry-level ratio of inventories over sales and the industry-level ratio of labor costs over sales. Industries with higher ratios can finance less of ongoing costs through revenues and hence might dependent more on external financing. Both measures are calculated from the NBER-CES manufacturing database.

Capital Intensity: More capital-intensive industries are expected to be more sensitive to changes in the user cost of capital, which itself will depend on changes in interest rates (Peersman and Smets (2005) and Bouakez, Cardia, and Ruge-Marcia (2013)). To control for this cost of capital channel, an industry's capital intensity is added as additional control variable. Following Peersman and Smets (2005), capital intensity is calculated as the ratio of capital expenditures over sales, using data from the NBER-CES manufacturing database over the time period 1988 to 2007.

Average Firm Size: Gertler and Gilchrist (1994) argue that small firms are more strongly affected by financial frictions than large firms and hence small firms are affected more strongly by monetary policy shocks than large firms. At the same time, large firms exhibit a higher frequency of price adjustment (Goldberg and Hellerstein (2009)). To control for industry-level differences in firm size, average firm size is added as additional control variable[22]. Average firm size is measured as the average number of employees per firm at the industry-level, calculated from the Economic Census 2007.

Interest-Rate Burden: Following Dedola and Lippi (2005), industries with higher interest rate expenses should be more exposed to changes in the interest rate. These industries should experience larger changes in costs following changes in interest rates. To control for this interest rate expense channel, the interest burden is added as additional control variable. The interest burden is calculated as the ratio of interest expenses over sales, using Compustat data from 1988 to 2007.

Leverage Ratio: D'Acunto, Liu, Pflueger, and Weber (2018) show that flexible price firms, on average, have a higher leverage ratio than sticky price firms. At the same time, Ottonello and Winberry (2018) show that at the firm level low leverage is associated with stronger (investment) responses to monetary policy shocks. In order to control for industry-level differences in leverage, I add industry-level leverage as additional control variable. Leverage is calculated as the ratio of total debt over total assets using Compustat data from 1988 to 2007.

Short-Term Debt Ratio: Industries with a larger share of short-term debt should be more exposed to changes in interest rates than industries with longer debt maturities, as they need to refinance debt more often. Hence industries with a larger share of short-term debt should experience a relatively larger change in the user cost of capital following changes in the interest rate. Following Dedola and Lippi (2005), the ratio of short-term debt over total assets is added as additional control variables. This variable is calculated using Compustat data from 1988 to 2007.

Standard Deviation of Output Growth: The size and frequency of idiosyncratic shocks might differ along industries as well. Industries facing more volatile idiosyncratic shocks might adjust prices more often, stay closer to their optimal price level and hence react less severely to monetary

[22]This variable enters regression 12 in logs, rather than in levels.

shocks (see e.g. Nakamura and Steinsson (2010)). Following Gorodnichenko and Weber (2016) the standard deviation of (monthly) output growth is added as additional control variable to control for the variance of idiosyncratic shocks. The standard deviation of output growth is calculated using the industry-level production data described in Section 2, over the time period December 1988 to December 2007.

Cyclicality: A further factor that might confound the effect of the frequency of price adjustment is the cyclicality of an industry (as noted in the beginning of this Section). When a contractionary policy shock causes economic activity to drop, more cyclical industries might experience a larger drop in output. At the same time, cyclical industries change prices more often (Klenow and Malin (2010)). To control for the cyclicality of an industry, the coefficient on total output growth estimated from a regression of (demeaned) monthly industry-level output growth on (demeaned) monthly total output growth is added as additional control variable. This coefficient is calculated using the monthly industrial production data described in Section 2 over the time period from 1988 to 2007.

Durable Goods Producers: Lastly, following Dedola and Lippi (2005), a dummy variable for industries producing durable goods is added, as durable goods producers might face more cyclical and more interest-rate sensitive demand.

I control for the additional variables described here in two separate ways. First, I report the results of a regression that includes only one of the control variables in addition to the frequency of price adjustment (and no other control variables), separately for every control variable. Furthermore, I estimate Equation 12 including all additional control variables jointly.

Table 3 and 4 shows the result for each of the regressions for the timing of $h = 24$ months after the shock.

Table 3: Price Stickiness and Monetary Policy Responses - Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Log(FPA)	0.545***	0.534**	0.471***	0.377**	0.348**	0.336**
	(0.181)	(0.228)	(0.172)	(0.164)	(0.149)	(0.146)
Inventory/Sales	2.374***					
	(0.795)					
Labor Costs/Sales		1.070				
		(1.464)				
Capital Intensity			-5.554			
			(4.534)			
Firm Size				-0.0595		
				(0.0767)		
Interest Expense Ratio					-1.489	
					(1.853)	
Leverage						0.227
						(0.598)
Observations	187	187	187	202	204	204
R-squared	0.060	0.044	0.047	0.033	0.034	0.032

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This Table reports the estimation results when estimating Equation 12 at a horizon of $h = 24$ months, including the additional control variables described in the text one at a time.

Table 4: Price Stickiness and Monetary Policy Responses - Additional Controls Cont.

	(1)	(2)	(3)	(4)	(5)
Log(FPA)	0.337**	0.319**	0.356**	0.257*	0.612***
	(0.148)	(0.147)	(0.150)	(0.154)	(0.235)
Inventory/Sales					2.880***
					(0.841)
Labor Costs/Sales					2.410
					(1.777)
Capital Intensity					-6.844
					(4.306)
Firm Size					0.0434
					(0.0804)
Interest Expense Ratio					-3.058
					(2.307)
Leverage					1.283*
					(0.748)
Short-Term Debt Ratio	-1.591				-2.096
	(1.690)				(2.013)
Cyclicality		-0.161**			-0.269***
		(0.0677)			(0.0813)
Std(Output Growth)			-0.0215		0.0416
			(0.0321)		(0.0499)
Durability				-0.245*	-0.243
				(0.138)	(0.175)
Observations	204	205	205	205	186
R-squared	0.034	0.055	0.033	0.045	0.149

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports the estimation results when estimating Equation 12 at a horizon of $h = 24$ months, including the additional control variables described in the text one at a time. In the last column all control variables described in the text are included jointly.

Table 3 and 4 show that the main finding established in Section 5 is not only robust to the inclusion of further industry characteristics, but the estimated coefficient on the frequency of price adjustment becomes even larger in most cases. When controlling for all other control variables jointly (Column 5 in Table 4), the coefficient on the frequency of price adjustment becomes nearly twice as large compared to the case when no other control variables are used (0.612 when including all other control variables vs 0.341 when no other control variables are used).

Table 5 shows that this is also the case for the horizons of $h = 18$ months and $h = 30$ months after the shock. Table 5 reports the results of Equation 12 when all other control variables are included jointly for the horizons of $h = 18$ months and $h = 30$ months. Similar to the case of $h = 24$ months after the shock, the coefficient on the frequency of price adjustment is now substantially larger than before (0.496 when including all other control variables vs 0.223 when no other control variables are included for the horizon $h = 18$ months after the shock, and 0.548 when including all other control variables vs 0.339 when no other control variables are included for the horizon $h = 30$ months after the shock).

Table 5: Price Stickiness and Monetary Policy Responses - Additional Controls at Different Horizons

	(1) $h = 18$ Months	(2) $h = 30$ Months
Log(FPA)	0.496**	0.548**
	(0.242)	(0.226)
Inventory/Sales	2.557***	2.340***
	(0.806)	(0.881)
Labor Costs/Sales	2.532	2.242
	(1.584)	(1.828)
Capital Int.	-5.785	-7.000
	(3.980)	(4.792)
Firm Size	0.0597	0.0606
	(0.0770)	(0.0788)
Interest Expense Ratio	-2.975*	-3.515
	(1.754)	(2.476)
Leverage	0.627	1.469**
	(0.711)	(0.741)
Short-Term Debt Ratio	-1.245	-2.419
	(1.824)	(2.008)
Cyclicality	-0.199***	-0.283***
	(0.0751)	(0.0796)
Std(Output Growth)	0.0144	0.0679
	(0.0478)	(0.0452)
Durability	-0.227	-0.167
	(0.161)	(0.175)
Observations	186	186
R-squared	0.112	0.152

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports the estimation results when estimating Equation 12 at horizons $h = 18$ months (column (1)) and $h = 30$ months (column (2)), respectively. All control variables described in the text are included jointly.

The results presented in this Section provides further support for the hypothesis that sticky price industries react more strongly to monetary policy shocks than flexible price industries. The results reported in Tables 3, 4 and 5 show that the differential output reactions in response to monetary policy shocks between sticky- and flexible-price industries established in Section 5 is not spuriously caused by omitted variable bias induced by a wide range of other industry characteristics controlled for in this Section. This finding is consistent with the prediction made by (multi-sector) New Keynesian models and suggests that sticky prices indeed play an important role in the monetary transmission mechanism. The results reported here alleviate concerns that the (cross-industry) correlation between the output response to monetary policy shocks and the frequency of price adjustment is spuriously caused by other industry characteristics. In fact, the findings reported in Tables 3, 4 and 5 rather suggest the opposite: when not controlling for the additional industry-level characteristics considered in this Section (as in Equation 11), the correlation between the output response and the frequency of price adjustment is attenuated towards zero.

Qualitatively, the result is unchanged compared to Section 5 - Industries with more sticky prices react more strongly to monetary policy shocks. Quantitatively, the results reported here suggest that the differential reaction between sticky and flexible price industries is even stronger as suggested by the results reported in Section 5.

7 Robustness

This Section further investigates the robustness of the results in two respects. First, I consider the robustness of the results with respect to the minimum delay restriction (i.e. the restriction that monetary shocks have no effect on industrial production on impact) imposed in the baseline estimation scheme. Furthermore, I consider the robustness of the results with respect to the identification of monetary policy shocks. To asses the robustness of the results in this dimension, I repeat the analysis using the identification scheme for monetary policy shocks of Miranda-Agrippino (2016).

As one robustness check, I relax the minimum delay restriction imposed in the baseline estimation scheme described in Sections 3 and 4. In this robustness check, I allow for an immediate effect of monetary policy shocks on the other variables in the system (most importantly on aggregate and sectoral industrial production). This is achieved by ordering the monetary policy shock as first variable in the VAR, allowing for an immediate reaction of all other variables[23]. To allow for an immediate reaction of (sectoral) output of industry i, matrix $A_{0,i}$ is changed to:

$$A_{0,i} = \begin{bmatrix} * & 0 & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & * & 0 & 0 \\ * & * & * & * & * & 0 \\ * & * & * & * & * & * \end{bmatrix} \tag{13}$$

which allows for an immediate reaction of industry i's output to a policy shock (and for an immediate reaction of (aggregate) industrial production in response to a monetary policy shock). In the following, I will refer to this robustness check as 'Alternative Ordering'.

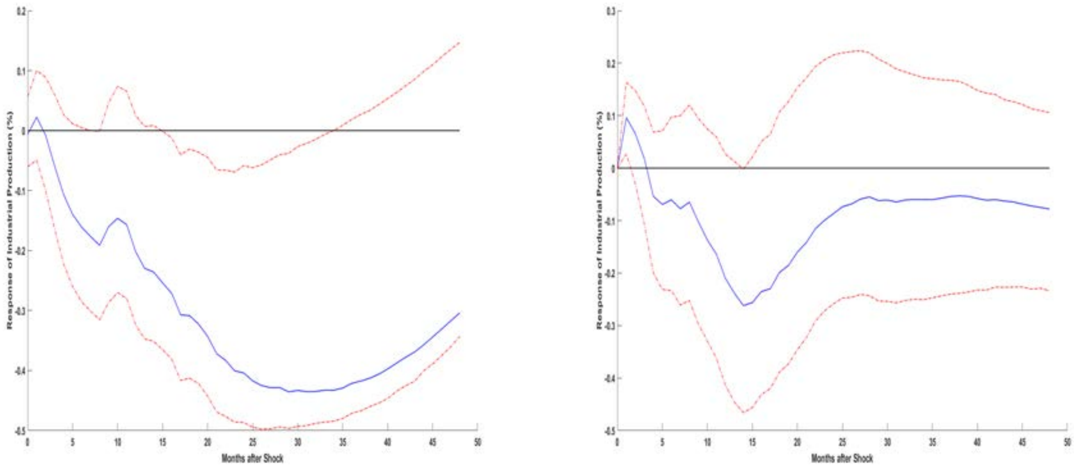
As further robustness check, I repeat the analysis using the monetary policy shock series of Miranda-Agrippino (2016). The identification scheme of Miranda-Agrippino (2016) is a hybrid approach of identifying monetary policy shocks, combining market-based measures of monetary policy shocks (like Barakchian and Crowe (2013) used above, or e.g. Gürkaynak, Sack, and Swanson (2005)) and the narrative approach of Romer and Romer (2004). One concern with the

[23] In terms of the notation used before, $Y_{t,i}$ is now given by $Y_{t,i} = [CSHOCK_t, IP_t, UNEMP_t, CPI_t, PCOM_t, OUT_{t,i}]^T$

financial market based identification approach of monetary shocks used in the baseline analysis is that the central bank might have superior information compared to financial market participants (as noted in Section 2). If this is the case, monetary policy decisions that are surprising to financial market participants might not be pure monetary shocks, but also convey new information to agents in the economy (see e.g. Jarocinski and Karadi (2018)). To control for this information effect, Miranda-Agrippino (2016) constructs a financial market based measure of monetary policy shocks that explicitly controls for the information set of the central bank. This approach combines the high-frequency identification of monetary policy shocks of Gertler and Karadi (2015) with the narrative identification of Romer and Romer (2004). Monetary policy shocks in Miranda-Agrippino (2016) are constructed as the residual of a regression of the high-frequency monetary policy shocks of Gertler and Karadi (2015) on the Fed Greenbook Forecast variables used by Romer and Romer (2004)[24]. In the robustness check using this identification of monetary policy shocks, the estimation of (aggregate and industry-specific) responses to monetary shocks is carried out as described in Section 3 and Section 4, replacing the shock series of Barakchian and Crowe (2013) with the shock series of Miranda-Agrippino (2016). In the following, I will refer to this robustness check as 'Alternative Shock Identification'.

[24]The monetary policy shock series constructed this way can be downloaded from the webpage of Silvia Miranda-Aggripino, avaiable at http://silviamirandaagrippino.com/code-data.

Figure 4: Response of Industrial Production to a Contractionary Monetary Policy Shock - Robustness Checks



(a) Alternative Ordering

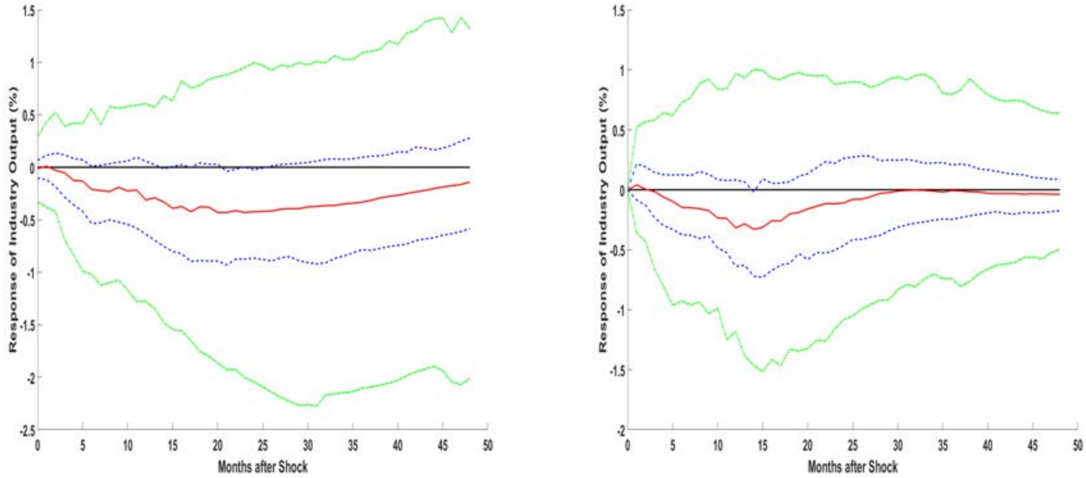
(b) Alternative Shock Identification

These Figures show the response of (aggregate) industrial production to a one standard deviation contractionary policy shock. The left Panel shows the results when the shock measure of Barakchian and Crowe (2013), but no minimum delay restriction is used. The right Panel shows the estimation results when the shock measure of Miranda-Agrippino (2016) is used. In both Panels, the blue line shows the point estimate of the IRF. The red, dashed lines show the 90% Confidence Interval based on 5000 Bootstrap replications.

Figure 4 depicts the estimated response of (aggregate) industrial production to a one standard deviation contractionary policy shock estimated in both robustness checks. The estimated responses of the other aggregate variables in the two robustness checks can be found in the Appendix in Figure 10 (alternative ordering) and Figure 11 (alternative shock identification), respectively. Relaxing the minimum delay restriction has barely any impact on the estimated response of industrial production, compared to the baseline estimation scheme. Regarding the estimation using the shock measure of Miranda-Agrippino (2016), two things are noteworthy. First, the peak response of industrial production to a contractionary monetary policy shock is reached faster (after approximately 15 months), compared to when the shock measure of Barakchian and Crowe (2013) is used. Second, the magnitude of the peak drop in (aggregate) industrial production in response to a contractionary shock is (comparatively) smaller. The estimated peak in the drop in industrial production in response to a one standard deviation contractionary shock is around 0.25% in this robustness check, smaller than the drop of 0.38% found when using the monetary shock series of Barakchian and Crowe (2013).

Figure 5 shows the distribution of sectoral (output) responses to a one standard deviation contractionary monetary policy shock estimated in both robustness checks described here. The left Panel in Figure 5 shows the distribution of estimated industry output responses when using monetary policy shocks identified as in Barakchian and Crowe (2013) and not imposing a minimum delay restriction. The right Panel in Figure 5 shows the distribution of estimated industry output responses when using monetary policy shocks identified as in Miranda-Agrippino (2016) and the baseline estimation scheme described in Section 4 is used.

Figure 5: Industry Responses to a Contractionary Monetary Policy Shock - Robustness Checks



(a) Alternative Ordering

(b) Alternative Shock Identification

These Figures show the output response of the 205 different industries to a one standard deviation contractionary policy shock. The left Panel shows the results when the shock measure of Barakchian and Crowe (2013), but no minimum delay restriction is used. The right Panel shows the estimation results when the shock measure of Miranda-Agrippino (2016) is used. In both Panels, the red line shows the median response of all industries at each horizon. The blue lines show the 25th and 75th percentile of the distribution of the industries output responses at each horizon. The green lines show the fifth and 95th percentile of the distribution of the industries output responses at each horizon.

Figure 5 shows that in both cases there is substantial heterogeneity present in the output response across industries. As before, roughly 25% of industries experience an increase in output in response to a contractionary policy shock in both robustness checks. When identifying monetary policy shocks as in Miranda-Agrippino (2016), industry output responses are smaller in magnitude and the peak response is reached more quickly compared to the results when using the shock measure of Barakchian and Crowe (2013), mirroring to the difference in the estimated reaction of aggregate industrial production across both estimation schemes described above. Otherwise, industry responses are very similar across the different estimation schemes discussed here. The cross-sectional correlation of industry responses between the baseline estimation in Section 4 and the two estimation schemes presented here is $\rho = 0.98$ (alternative ordering) and $\rho = 0.59$ (different shock identification) at a horizon of $h = 24$ months, respectively.

The regression results obtained in the two robustness checks when including no other control variables (i.e. as described in Section 5) can be found in Table 6. Consistent with the results reported in Section 5, I report the estimates using the cross-section of industry responses $h = 18$, 24 and 30 months after a contractionary policy shock. Columns labeled (1), (2) and (3) in Table 6 report the results of the alternative ordering robustness check. Columns labeled (4), (5) and (6) in Table 6 report the results of the alternative shock identification robustness check.

Table 6: Price Stickiness and Monetary Policy Responses - Robustness Checks

	(1) $h = 18$	(2) $h = 24$	(3) $h = 30$	(4) $h = 18$	(5) $h = 24$	(6) $h = 30$
Log(FPA)	0.255* (0.152)	0.364** (0.158)	0.357** (0.147)	0.573*** (0.169)	0.361*** (0.106)	0.0620 (0.0780)
Observations	205	205	205	205	205	205
R-squared	0.017	0.030	0.033	0.131	0.066	0.002
$I\bar{R}F^h$	-0.308	-0.404	- 0.433	-0.199	-0.087	- 0.061

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports the coefficient on log(FPA) in regression 11 at different horizons h after the shock. The constant term is not reported. Columns labeled (1), (2) and (3) report the results of the alternative ordering robustness check. Columns labeled (4), (5) and (6) report the results of the alternative shock identification robustness check. $I\bar{R}F^h$ denotes the response of the (total) industrial production index h months after an unexpected one standard deviation increase in the policy measure, estimated in the same robustness check. Robust standard errors are reported in Parenthesis.

The results obtained in the alternative ordering robustness check (reported in the Columns labeled (1), (2) and (3) of Table 6) are nearly identical to the baseline results reported in Table 1. The results obtained when identifying monetary policy shocks as in Miranda-Agrippino (2016) (reported in the Columns labeled (4), (5) and (6) in Table 6) suggest a stronger association between the frequency of price adjustment and the output response to monetary policy shocks, compared to the baseline results. In this robustness check, the estimated coefficient on the frequency of price adjustment is larger, while the drop in industrial production is smaller.[25]

Table 7: Price Stickiness and Monetary Policy Responses - Additional Controls in Robustness Checks

	(1) $h = 18$	(2) $h = 24$	(3) $h = 30$	(4) $h = 18$	(5) $h = 24$	(6) $h = 30$
Log(FPA)	0.547**	0.653***	0.590**	0.717**	0.530***	0.208*
	(0.252)	(0.250)	(0.241)	(0.306)	(0.180)	(0.120)
Observations	186	186	186	186	186	186
R-squared	0.115	0.149	0.155	0.203	0.131	0.100
Add. Controls	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports the coefficient on log(FPA) in regression 12 at different horizons h after the shock. The constant term is not reported. Columns labeled (1), (2) and (3) report the results of the alternative ordering robustness check. Columns labeled (4), (5) and (6) report the results of the alternative shock identification robustness check. In all results the full set of industry-level control variables described in Section 6 is included. Robust standard errors are reported in Parenthesis.

[25]When comparing the results obtained in the different shock identification robustness check with the baseline results, it should also be kept in mind that when using the identification scheme of Miranda-Agrippino (2016), the peak in the drop of industrial production is reached faster. For the sake of comparing the size of the coefficients obtained in this (alternative shock identification) robustness check to the baseline results, it is also helpful to consider the standardized regression coefficient obtained from regression 11 (i.e. standardizing all variables to have mean zero and a standard deviation of one before estimating the regression). The standardized regression coefficients obtained in the baseline results are $\beta^{h=18} = .123$ and $\beta^{h=24} = .175$ for $h = 18$ and $h = 24$ months, respectively. The interpretation of e.g. $\beta^{h=24} = .175$ is that a one standard deviation increase in the log of the frequency of price adjustment is associated with a 0.175 standard deviation increase in the output reaction to a contractionary monetary policy shock at a horizon of 24 months after the shock (in the baseline results reported in Section 5). In the alternative shock identification robustness check, the standardized regression coefficients are estimated at $\beta^{h=18} = .361$ and $\beta^{h=24} = .257$ at the two horizons, respectively. Using this standardized measure, the (relative) size of the association between the frequency of price adjustment and the output reaction to monetary policy shocks is approximately twice as large in the alternative shock identification robustness check, compared to the baseline result.

Table 7 reports the results obtained in the respective robustness checks when controlling for all additional industry-level variables described in Section 6.[26] These results confirm the finding established in Section 6: When controlling for additional industry characteristics, the correlation between the frequency of price adjustment and an industry's output response to monetary policy shocks becomes larger compared to the case where no additional industry-level variables are considered.

Both robustness checks confirm a significant association between the frequency of price adjustment and the output response to monetary policy shocks at the industry level. The results obtained in the robustness checks suggest that the association between the frequency of price adjustment and the output response to monetary policy shocks at the industry level is rather under- than overestimated in the main specification. This alleviates concerns that the established association is spuriously caused by the estimation method, the identification of monetary policy shocks or by omitted industry characteristics. The results suggest that sticky prices indeed play a central role the monetary transmission mechanism, consistent with the predictions of (multi-sector) New Keynesian models.

8 Conclusion

Do sticky prices matter for the monetary transmission mechanism? This paper provides new evidence on this question by studying the role of price stickiness for the monetary transmission mechanism using disaggregated industry-level data from 205 US manufacturing industries. The output reactions of different industries to a (common) contractionary monetary policy shock differ substantially. Two years after a one standard contractionary monetary policy shock, (total) industrial production is estimated to drop by approximately 0.38%. Some industries experience a drop in output as large as 2%, while other industries even increase output by 0.9% in reaction to the same shock, at the same horizon.

I show that an industry's output response to monetary policy shocks is systematically related to the industry's degree of price stickiness. Price stickiness is measured via the industry-level frequency of price adjustment, calculated from PPI microdata. Industries with a higher frequency of price adjustment (i.e. less sticky prices) experience a smaller drop in output than industries with a lower frequency frequency of price adjustment (i.e. more sticky prices) in reaction to the

[26]Table 10 (alternative ordering) and Table 11 (alternative shock identification) in the Appendix report the coefficients on all variables included in the estimation.

same contractionary monetary policy shock. The association between an industry's frequency of price adjustment and the output reaction to monetary policy shocks is statistically significant and the size of the differential reaction is economically relevant. A 10% increase in the frequency of price adjustment is associated with a reduction in the output drop in response to a contractionary monetary policy shock that is approximately as large as 10% of the drop in total industrial production. This result is robust to the inclusion of various industry-level control variables, intended to capture alternative transmission channels of monetary policy.

Qualitatively, the results established in this paper are consistent with predictions of multi-sector New Keynesian models. Quantitatively, the results provide empirical support for the New Keynesian view that sticky prices indeed play an important quantitative role in the transmission of monetary policy to real economic activity. Sticky prices indeed matter for the monetary transmission mechanism. While the association between an industries degree of price stickiness and the reaction to monetary policy shocks documented in this paper provides no direct evidence on the degree of aggregate monetary non-neutrality, the results established in this paper can be used to discipline multi-sector New Keynesian models to provide new evidence on this classical question.

References

Balleer, A., N. Hristov, and D. Menno (2017): “Financial Constraints and Nominal Price Rigidities,” *CESifo Working Paper No. 6309*, (6309).

Barakchian, S. M., and C. Crowe (2013): “Monetary Policy Matters: Evidence from New Shocks Data,” *Journal of Monetary Economics*, 60(8), 950 – 966.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999): “The Financial Accelerator in a Quantitative Business Cycle Framework,” in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, vol. 1, chap. 21, pp. 1341 – 1393. Elsevier.

Bils, M., and P. J. Klenow (2004): “Some Evidence on the Importance of Sticky Prices,” *Journal of Political Economy*, 112(5), 947– 985.

Bouakez, H., E. Cardia, and F. Ruge-Marcia (2013): “Sectoral Price Rgidity and Aggregate Dynamics,” *European Economic Review*, 65, 1 – 22.

Calvo, G. (1983): “Staggered Prices in a Utility Maximizing Framework,” *Journal of Monetary Economics*, 12(3), 383 – 398.

Caplin, A. S., and D. F. Spulber (1987): “Menu Costs and the Neutrality of Money,” *The Quarterly Journal of Economics*, 102(4), 703–726.

Carlino, G., and R. DeFina (1998): “The Differential Regional Effects of Monetary Policy,” *Review of Economics and Statistics*, 80(4), 572–587.

Christiano, L., M. Eichenbaum, and C. Evans (1999): “Monetary Policy Shocks: What Have We Learned and to What End?,” in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, vol. 1, chap. 2, pp. 65–148. Elsevier.

Coibion, O. (2012): “Are the Effects of Monetary Policy Shocks Big or Small?,” *American Economic Journal: Macroeconomics*, 4(2), 1–32.

D’Acunto, F., R. Liu, C. Pflueger, and M. Weber (2018): “Flexible Prices and Leverage,” *Journal of Financial Economics*, 129(1), 46–88.

Davis, S. J., and J. Haltiwanger (2001): “Sectoral Job Creation and Destruction Responses to Oil Price Changes,” *Journal of Monetary Economics*, 48(3), 465–512.

Dedola, L., and F. Lippi (2005): "The Monetary Transmission Mechanism: Evidence from the Industries of Five OECD Countries," *European Economic Review*, 49(6), 1543–1569.

Galí, J. (2015): *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and Its Applications.* Princeton University Press, 2 edn.

Ganley, J., and C. Salmon (1997): "The Industrial Impact of Monetary Policy Shocks: Some Stylised Facts," *Bank of England Working Paper No. 68.*

Gertler, M., and S. Gilchrist (1994): "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109(2), 309 – 340.

Gertler, M., and P. Karadi (2015): "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7(1), 44–76.

Ghassibe, M. (2018): "Monetary Policy and Production Networks: An Empirical Investigation," *ECB Forum on Central Banking.*

Goldberg, P. K., and R. Hellerstein (2009): "How Rigid are Produer Prices?," *Federal Reserve Bank of New York Staff Report no. 407.*

Golosov, M., and R. E. Lucas (2007): "Menu Costs and Phillips Curves," *Journal of Political Economy*, 115(2), 171–199.

Gorodnichenko, Y., and M. Weber (2016): "Are Sticky Prices Costly? Evidence from the Stock Market," *American Economic Review*, 106(1), 165–199.

Gürkaynak, R. S., B. Sack, and E. Swanson (2005): "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1(1), 55 – 93.

Hayo, B., and B. Uhlenbrock (2000): "Industry Effects of Monetary Policy in Germany," in *Regional Aspects of Monetary Policy in Europe*, ed. by J. von Hagen, and C. J. Waller, pp. 127–158. Springer.

Hong, G. H., M. Klepacz, E. Pasten, and R. Schoenle (2020): "The Real Effects of Monetary Shocks: Evidence from Micro Pricing Moments," Working Papers Central Bank of Chile 875, Central Bank of Chile.

Jarocinski, M., and P. Karadi (2018): "Deconstructing Monetary Policy Surprises: The Role of Information Shocks," *CEPR Disucssion Paper No. 12765.*

Klenow, P., and B. Malin (2010): "Microeconomic Evidence on Price-Setting," in *Handbook of Monetary Economics*, ed. by B. M. Friedman, and M. Woodford, vol. 3, chap. 6, pp. 231–284. Elsevier.

Miranda-Agrippino, S. (2016): "Unsurprising Shocks: Information, Premia, and the Monetary Transmission," *Centre for Macroeconomics, Discussion Paper n. 2016-13.*

Nakamura, E., and J. Steinsson (2008): "Five Facts about Prices: A Reevaluation of Menu Cost Models," *The Quarterly Journal of Economics*, 123(4), 1415–1464.

——— (2010): "Monetary Non-Neutrality in a Multisector Menu Cost Model," *The Quarterly Journal of Economics*, 125(3), 961 – 1013.

Ottonello, P., and T. Winberry (2018): "Financial Heterogeneity and the Investment Channel of Monetary Policy," *NBER Working Paper No. 24221.*

Pasten, E., R. Schoenle, and M. Weber (2018a): "Price Rigidity and the Origins of Aggregate Fluctuations," *NBER Working Paper No. 23750.*

——— (2018b): "The Propagation of Monetary Policy Shocks in a Heterogeneous Production Economy," *NBER Working Paper No. 25303.*

Peersman, G., and F. Smets (2005): "The Industry Effects of Monetary Policy in the Euro Area," *The Economic Journal*, 115(503), 319–342.

Raddatz, C. (2006): "Liquidty Needs and Vulnerability to Financial Underdeveloptment," *Journal of Financial Economics*, 80(3), 677–722.

Ramey, V. A. (2016): "Macroeconomic Shocks and Their Propagation," in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and H. Uhlig, vol. 2, chap. 2, pp. 71–162. Elsevier.

Romer, C. D., and D. H. Romer (2004): "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, 94(4), 1055–1084.

Söderström, U. (2001): "Predicting Monetary Policy with Federal Funds Futures Prices," *Journal of Futures Markets*, 21(4), 377 – 391.

A Detail on the Construction of Industry-Level Control Variables

This section describes the calculation of the industry-level control variables presented in Table 2 in Section 6. The exact calculation procedure of the variables is explained separately for every data source.

Variables calculated from the NBER-CES manufacturing database and (denoted as NBER-CES in Table 2) are calculated in two steps. First, the industry average (of the respective variable) is calculated separately for every year of the data. Industry-level averages of ratios are always calculated by first calculating industry-level totals of variables used in the calculation of the ratio, and then taking the ratio of the industry-level totals of the respective variables. In a second step, the final control variable is calculated as the time average of the yearly industry-averages in the sample.

Variables calculated based on yearly Compustat data are calculated in a similar fashion. First, firm-level observations are aggregated to the industry-level separately for every year of the data. This is done by summing firm-level variables at the industry-level. Ratios are then calculated based on industry-level totals of the variables. The final industry-level control variables are calculated as the time average of the yearly industry-level observations over all sample years. Following Ottonello and Winberry (2018), firms with a leverage ratio larger than 10 are dropped from the sample. Only US-based firms are used to calculate industry-level variables.

B Additional Tables

Table 8: Detailed Summary Statistics for the Frequency of Price Adjustment

	N	mean	sd	min	max	p5	p10	p25	p50	p75	p90	p95
FPA	205	23.37	14.20	4.011	87.53	9.797	11.52	15.08	19.22	25.89	41.68	52.28

This Table reports the summary statistics for the frequency of price adjustment (FPA) at the industry level. p5 to p95 denote the respective percentiles of the distribution within the sample.

Table 9: Summary Statistics for Additional Control Variables

	(1) N	(2) mean	(3) sd	(4) p5	(5) p95
Frequency of Price Adjustment	205	23.37	14.20	9.797	52.28
Durable Goods Dummy	205	0.522	0.501	0	1
Capital intensity	187	0.0312	0.0158	0.0114	0.0631
Inventory/Sales	187	0.124	0.0641	0.0443	0.202
Labor Cost over Sales	187	0.163	0.0709	0.0576	0.274
Firm Size	202	116.2	129.8	19.34	362.3
Leverage	200	0.595	0.126	0.386	0.796
Interest Expense Ratio	202	0.0359	0.0387	0.0104	0.122
Short-Term Debt Ratio	202	0.0588	0.0326	0.0236	0.125
Cyclicality	205	0.917	0.948	-0.0770	2.798
Standard Dev. of Output Growth	205	3.272	2.144	1.144	7.866

This Table reports the summary statistics for the additional industry-level control variables.

Table 10: Price Stickiness and Monetary Policy Responses - Alternative Ordering Robustness Check

	(1) $h = 18$ Months	(2) $h = 24$ Months	(3) $h = 30$ Months
Log(FPA)	0.547**	0.653***	0.590**
	(0.252)	(0.250)	(0.241)
Inventory/Sales	2.817***	3.093***	2.526***
	(0.867)	(0.913)	(0.960)
Labor Costs/Sales	2.699	2.533	2.425
	(1.705)	(1.931)	(1.991)
Capital Int.	-5.000	-6.346	-6.597
	(4.169)	(4.496)	(4.959)
Firm Size	0.0510	0.0276	0.0388
	(0.0833)	(0.0864)	(0.0833)
Interest Expense Ratio	-3.184	-3.468	-4.105
	(1.979)	(2.490)	(2.600)
Leverage	0.773	1.485*	1.712**
	(0.775)	(0.809)	(0.790)
Short-Term Debt Ratio	-1.960	-2.710	-2.805
	(2.074)	(2.269)	(2.257)
Cyclicality	-0.215***	-0.283***	-0.297***
	(0.0821)	(0.0883)	(0.0865)
Std(Output Growth)	0.0129	0.0422	0.0741
	(0.0524)	(0.0541)	(0.0484)
Durability	-0.269	-0.281	-0.194
	(0.175)	(0.189)	(0.187)
Observations	186	186	186
R-squared	0.115	0.149	0.155

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This Table reports the estimation results when estimating Equation 11 at different horizons h in the Alternative Ordering Robustness Check. The constant term is not reported. Robust standard errors are reported in Parenthesis.

Table 11: Price Stickiness and Monetary Policy Responses - Different Shock Identification Robustness Check

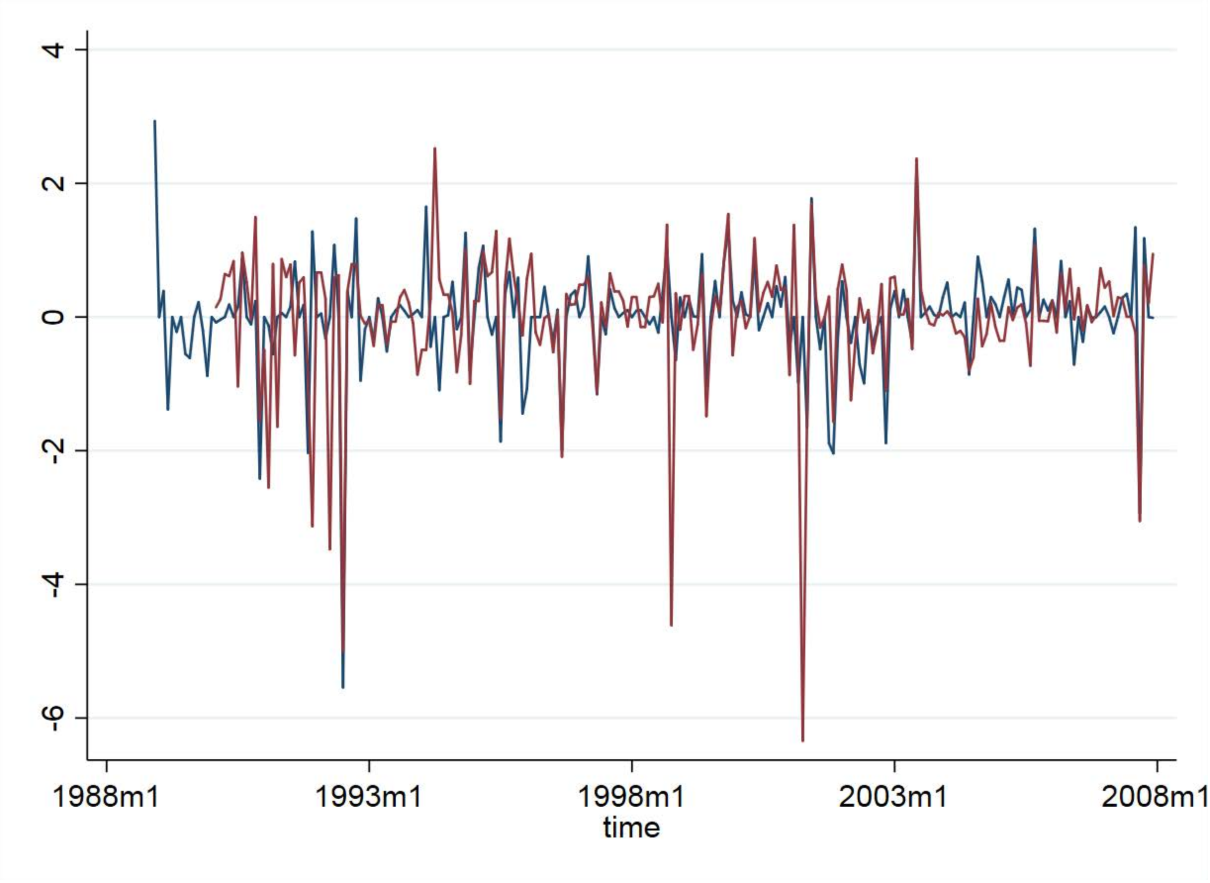
	Title		
	(1)	(2)	(3)
	$h = 18$ Months	$h = 24$ Months	$h = 30$ Months
Log(FPA)	0.717**	0.530***	0.208*
	(0.306)	(0.180)	(0.120)
Inventory/Sales	1.685	0.234	-0.175
	(1.126)	(1.085)	(0.720)
Labor Costs/Sales	0.419	1.253	1.884*
	(1.211)	(0.986)	(0.982)
Capital Int.	-4.302	-6.158	-10.57*
	(3.920)	(3.872)	(5.384)
Firm Size	0.0915	0.0733	0.0689
	(0.0951)	(0.0813)	(0.0663)
Interest Expense Ratio	0.595	-1.529	-2.320*
	(2.075)	(1.766)	(1.377)
Leverage	0.579	0.684	0.985**
	(0.642)	(0.550)	(0.461)
Short-Term Debt Ratio	-2.614	-1.566	-2.281
	(1.624)	(1.535)	(1.897)
Cyclicality	-0.101*	-0.0488	-0.0245
	(0.0554)	(0.0549)	(0.0489)
Std(Output Growth)	-0.0309	0.00504	0.0253
	(0.0367)	(0.0317)	(0.0278)
Durability	-0.0765	-0.0935	-0.0849
	(0.111)	(0.113)	(0.109)
Observations	186	186	186
R-squared	0.203	0.131	0.100

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This Table reports the estimation results when estimating Equation 11 at different horizons h in the Alternative Shock Identification Robustness Check. The constant term is not reported. Robust standard errors are reported in Parenthesis.

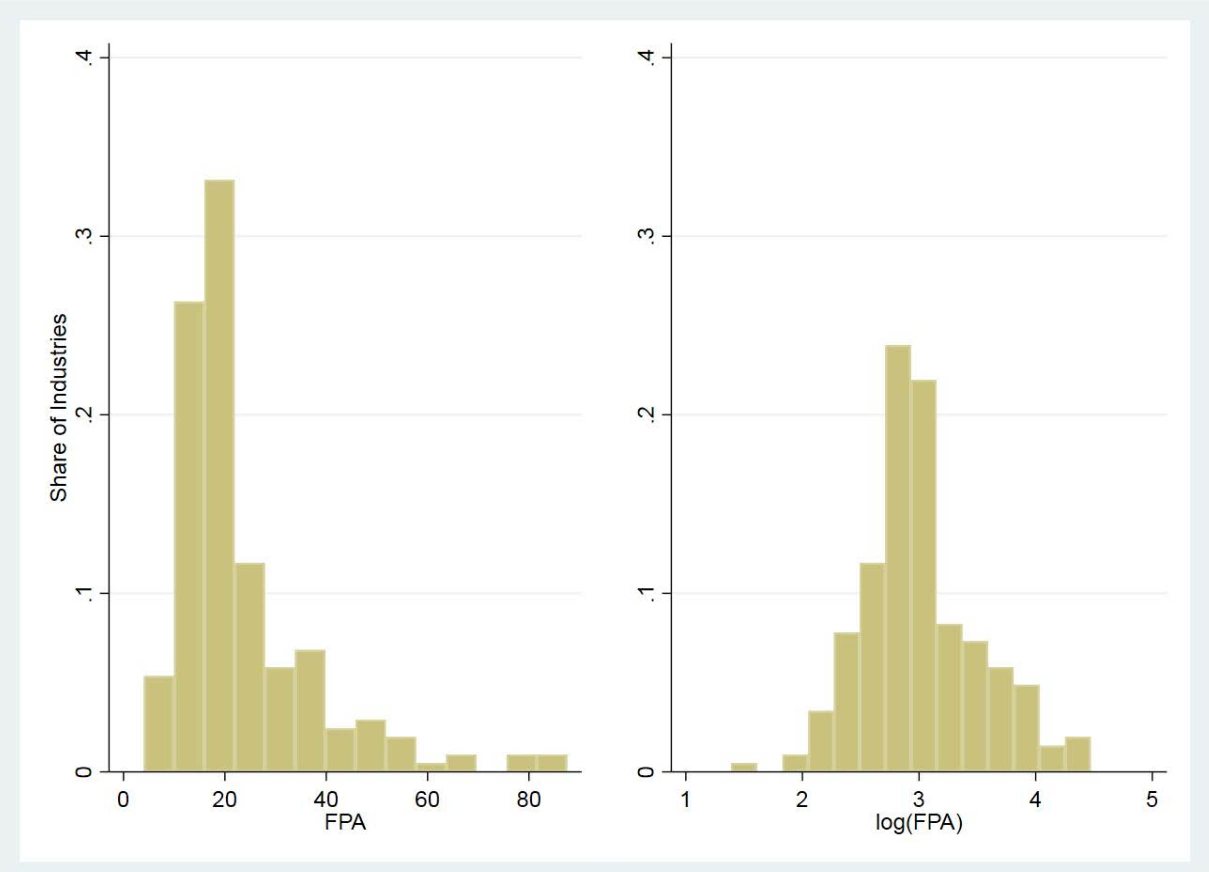
C Additional Figures

Figure 6: Monetary Policy Shock Series



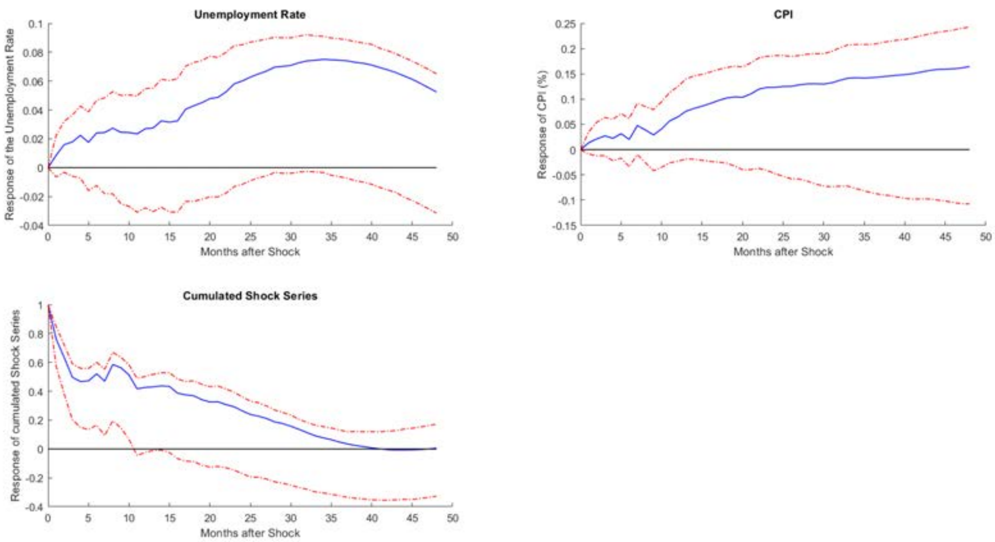
This Figure shows the time series of the monetary policy shock series used in the paper. The blue line is the monetary shock series of Barakchian and Crowe (2013). The red line shows the shock series of Miranda-Agrippino (2016). Both series are standardized with mean zero and a standard deviation of one. The y-axis is expressed in units of standard deviations of the shock.

Figure 7: Distribution of the Frequency of Price Adjustment



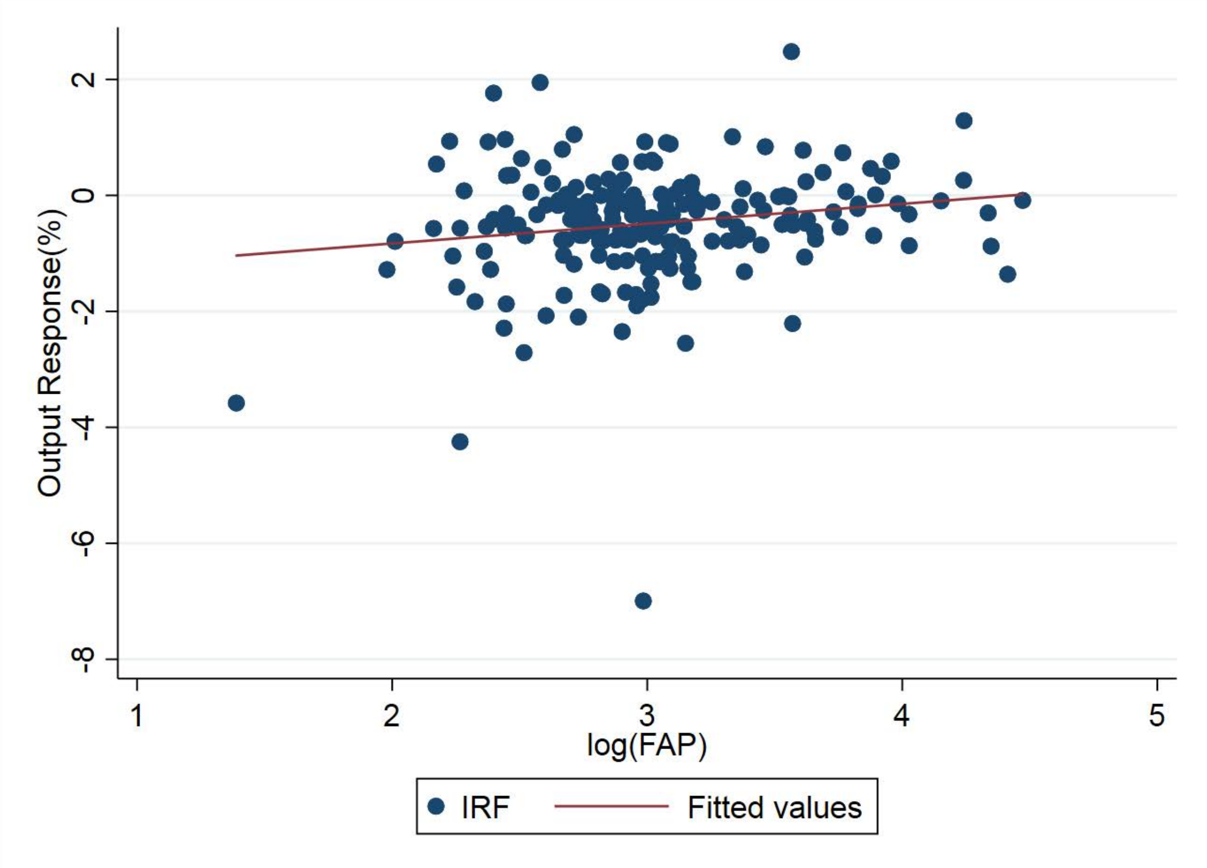
This Figure shows the with-in sample distribution of the frequency of price adjustment (FPA, left Panel) and the log of the frequency of price adjustment (right Panel).

Figure 8: Response of other Variables to a contractionary Policy Shock



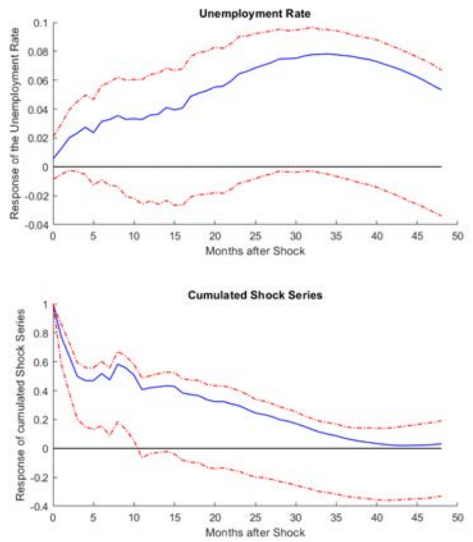
Structural VAR (Monthly data, 5 endogenous variables, 12 lags). Variables ordered as industrial production (in logs), unemployment rate, consumer price index (in logs), commodity price index (in logs) (all seasonally adjusted) and the cumulated shock measure of Barakchian and Crowe (2013). Graphs show the responses of the variables in the system (excluding industrial production) to a one standard deviation increase to the policy measure. Structural shocks obtained via Cholesky decomposition. Bootstrapped 90% Confidence Intervals based on 5000 Bootstrap Replications are shown in the red, dotted lines.

Figure 9: Scatter Plot of Industry Responses 24 Months after the Policy Shock vs log(FPA)



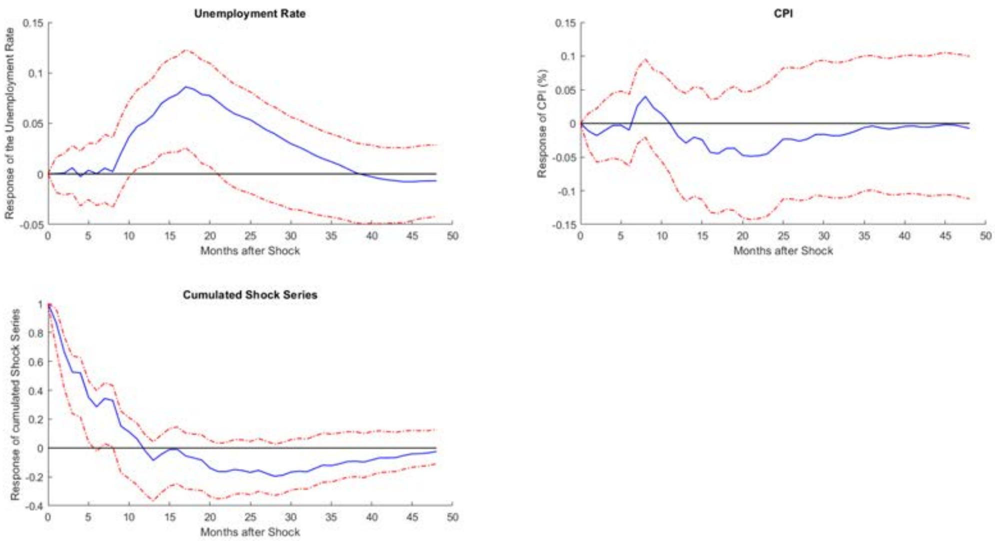
This Figure shows the scatter plot of the cumulative output response of the 205 different industries to a one standard deviation contractionary policy shock at a horizon of 24 Months after the shock plotted against the log of the frequency of price adjustment of the industry. Each blue dot represents a single industry. On the X-axis, the log of the frequency of price adjustment is shown. On the Y-Axis, the cumulative output response, reported in percent, to a one Standard Deviation contractionary Policy Shock is shown, 24 Months after the shock has happened. The red line shows the linear fit.

Figure 10: Responses to a Contractionary Policy Shock - Alternative Ordering



Structural VAR (Monthly data, 5 endogenous variables, 12 lags). Variables ordered as the cumulated shock measure of Barakchian and Crowe (2013), industrial production (in logs), unemployment rate, consumer price index (in logs), and a commodity price index (in logs) (all seasonally adjusted). Graphs show the responses of the variables in the system to a one standard deviation increase to the policy measure. Bootstrapped 90% Confidence Intervals based on 5000 Bootstrap Replications are shown in the red, dotted lines.

Figure 11: Responses to a Contractionary Policy Shock - Different Shock Identification



Structural VAR (Monthly data, 5 endogenous variables, 12 lags). Variables ordered as industrial production (in logs), unemployment rate, consumer price index (in logs), commodity price index (in logs) (all seasonally adjusted) and the cumulated shock measure of Miranda-Agrippino (2016). Graphs show the responses of the variables in the system to a one standard deviation increase to the policy measure. Structural shocks obtained via Cholesky decomposition. Bootstrapped 90% Confidence Intervals based on 5000 Bootstrap Replications are shown in the red, dotted lines.

Acknowledgements

The views expressed here are my own and do not reflect those of the ECB and the Eurosystem. I am very thankful to Klaus Adam, Yuriy Gorodnichenko, Johannes Peifer and Matthias Meier for useful discussions and support. I am especially thankful to Michael Weber for providing data on industry-level price stickiness to me.

Lukas Henkel
European Central Bank, Frankfurt am Main, Germany; email: lukas.henkel@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

PDF ISBN 978-92-899-4390-1 ISSN 1725-2806 doi:10.2866/903108 QB-AR-20-125-EN-N