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The Financial Stability Dark Side of Monetary Policy

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Abstract

Market risk premia play an important role in the transmission of monetary policy. If the transmission were to work asymmetrically for positive and negative shocks, monetary authorities would face a problematic trade-off: a temporary stimulus could boost the economy in the short run, but at the same time sow the seeds of a painful medium-run market reversal (the "financial stability dark side" of monetary policy of Stein, 2014). We study the relation between interest rates, credit spreads and output in the U.S. using monthly data and a range of nonlinear dynamic models. We find clear signs of a reduced-form asymmetry, but no evidence in support of the causal mechanism that underpins the 'dark side' argument: spreads rise noticeably ahead of economic slowdowns but they do not appear to cause them directly, particularly if they move in response to monetary shocks. This suggests that the asymmetry is best interpreted as a purely predictive relation, with markets being particularly sensitive to bad economic news; and that it creates no complications for monetary policy or for the exit strategy from monetary accommodation.

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Keywords: risk premia; asymmetry; monetary policy; financial stability; local projections.

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1 Introduction

Credit markets are an important link in the transmission mechanism of monetary policy and are central to the interaction between monetary and macroprudential policy. Expansionary monetary shocks stimulate economic activity through an easing of financial conditions, possibly via a search-for-yield mechanism, and prolonged phases of excessively low interest rates have indeed been historically associated with high risk appetite, booming asset prices and positive output gaps (Borio and Zhu, 2012; Adrian and Liang, 2014; Buch *et al.*, 2014; Gertler and Karadi, 2015). Although the nature of this mechanism is the same for positive and negative policy shocks, the real effects of such shocks may differ in quantitative terms. The transmission could be asymmetric, with a tightening in credit conditions having a stronger impact on economic activity than a loosening of the same magnitude. Such an asymmetry arises endogenously, for instance, in models with a constraint on equity issuance (Brunnermeier and Sannikov, 2014) or in setups where collateral constraints are occasionally binding (Guerrieri and Iacoviello, 2013). Since monetary shocks only have a temporary effect on credit markets, such an asymmetry would place the authorities in a difficult position: expansionary policy shocks would stimulate the economy in the short–run but generate an opposite and larger effect in the longer run, all in all resulting in higher macroeconomic volatility and potentially financial instability. This is what (Stein, 2014) indicates as the "financial stability dark side" associated to monetary interventions.[1]

This paper provides an empirical investigation of the nonlinearities that underpin the "dark side" argument. Using the corporate bond spreads constructed by Gilchrist and Zakrajsek (2012) to capture credit conditions, we study the linkage between monetary policy, credit markets and economic activity in the US in the period between 1973 and 2012. The idea that the correlation between credit conditions and the real economy is asymmetric, and that often "good news is no news" in financial markets, is a popular one. Yet causality is central to the question at hand: a policy trade-off can only arise if (i) credit market fluctuations have an asymmetric impact on economic activity, and/or (ii) markets respond asymmetrically to positive and negative monetary shocks in the first place. To study these possibilities we start from simple predictive regressions and then move on to multivariate nonlinear models, where local projection methods (Jorda, 2005) can be used to study the dynamics associated to interpretable economic shocks. In this context we look at the transmission of both credit shocks and monetary shocks identified with the external instrument strategy of (Gertler and Karadi, 2015).

We find that changes in bond spreads have indeed a stronger predictive power for economic downturns than for expansions. Yet, once we isolate variations in spreads that are either

[1]See also Kocherlakota (2014) The issue is central to the debate on both the role of monetary policy in the run up to the 2008 financial crisis and the risks associated to Quantitative Easing, Bernanke (see 2015); Krugman (see 2015).

exogenous or caused by monetary policy, we find no evidence of a nonlinear impact of credit conditions on output. This rules out hypothesis (i). The response of credit markets to monetary shocks is economically important but again linear, thus ruling out hypothesis (ii) as well. Our reading of these results is that the reduced-form (predictive) asymmetry is largely the product of reverse causation, and that bond spreads simply tend to rise significantly ahead of cyclical downturns rather than causing them in any sense. On this regard, we provide simple but clean econometric evidence of EBP reacting asymmetrically to macroeconomic surprises *à* la Faust *et al.* (2007): credit spreads are found to be strongly sensitive to *bad* news, whereas the do not significantly move in response to *good* news.

Our work adds to the literature on the interaction between monetary policy and financial stability (see, e.g. Smets, 2014, for a review); it corroborates the existence of a reach–for–yield effect of monetary policy in credit markets (Bekaert *et al.*, 2013; Gertler and Karadi, 2015); and it tests whether this mechanism could make the exit from a long period of lose money and low spreads particularly costly, taking up a suggestion advanced by Stein (2014) and Lopez-Salido *et al.* (2016). Our key conclusion is that concerns of this nature should play at best a marginal role in setting the course of monetary policy.

The remainder of the paper is organized as follows. In section 2 we discuss the literature and use a stylized two-period model to illustrate why an asymmetric transmission mechanism creates a trade-off for monetary policy. In section 3 we describe the data used in the empirical analysis. In section 4 we examine a set of non–linear forecasting regressions where economic activity is regressed on the lagged bond spread, and this is allowed to enter the model asymmetrically (in particular, we resort to "local peak" functions to isolate in the data episodes where spreads reached high levels by historical standards). We then move to multivariate structural models. In section 5 we sketch our application of the local projection method and our identification strategies, while section 6 presents the results in terms of impulse response functions. In section 7 we check the robustness of our main conclusions along a number of directions, including the role of confidence, uncertainty and alternative measures of financial distress. In section 8, we reconcile the evidence between reduced–form and structural models. Finally, section 9 concludes. In the annex to the paper we provide supplementary material and we show that our conclusions also hold for the main euro area economies (where, if anything, the evidence in favor of a nonlinear transmission mechanism is even weaker than in the US).

2 The Dark Side Argument

This Section comprises two different parts. In the first one we briefly sketch Stein's (2014) "dark side" argument and reference the related literature. In the second one we use a toy model to give a flavour of the trade–off faced by a central bank in a world where the linkage between credit markets and real economy is nonlinear.

2.1 Literature

The mechanism at the heart of Stein (2014) “dark side" argument describes a causal chain that goes from monetary policy to market risk premia and from these to aggregate economic activity. As Stein (2014) points out, a nonlinearity must be present somewhere in this chain in order for a policy trade-off to arise: *for there to be such a dark side, there would have to be some sort of asymmetry in the unwinding of the effects of monetary policy on these risk premiums, whereby the eventual reversal either happens more abruptly, or causes larger economic effects, than the initial compression (p.10).*

The first link in this chain has been studied in the context of the "risk taking channel" of monetary policy (Borio and Zhu, 2012).[2] Most of the literature takes a banking perspective, exploiting bank- or loan-level data to study the relation between monetary policy and risk taking by financial intermediaries. The results suggest that banks typically soften their lending standards, demand lower premia and/or engage in riskier forms of investment in periods of easy monetary policy (see Jiménez *et al.*, 2014, and references therein). (Analogous mechanisms have been recently found to be active in equity markets (Bekaert *et al.*, 2013) and bond markets (Gertler and Karadi (2015)). Using high frequency data, Gertler and Karadi (2015) find that monetary interventions have a small impact on short-term risk-free rates but a fairly large impact on term and credit risk premia on corporate bonds, and that this second channel accounts for most of their overall macroeconomic effect. In particular, the Excess Bond Premium of Gilchrist and Zakrajsek (2012), which we define more precisely in section 3, is found to be highly sensitive to the U.S. monetary policy stance. The EBP is also a good predictor of economic activity in the U.S. (Gilchrist and Zakrajsek, 2012), which makes it a natural candidate for our empirical work. Woodford (2012) demonstrates that, if risk premia follow nonlinear dynamics (a Markov process) and are subject to large upward jumps, the policy maker faces a mean-variance trade-off even in a world where the link between spreads and output is linear, as suggested by the quote above. Chabot (2014) finds little evidence of asymmetric dynamics in a range of credit spreads in the U.S., including EBP. The possibility that bond spreads respond asymmetrically to (properly identified) monetary shocks, however, has not yet been investigated. By doing it, in the empirical section, we integrate the results in Bekaert *et al.* (2013) and Gertler and Karadi (2015) along an important dimension.

The nexus between financial markets and real economy - the second link in the chain - is the subject of a growing theoretical and empirical literature. There is little doubt by now that in general financial shocks play an important role in causing business cycle fluctuations (Christiano *et al.*, 2014; Nolan and Thoenissen, 2009; Gilchrist and Zakrajsek, 2012; Jermann and Quadrini, 2012; Liu *et al.*, 2013; Gambetti and Musso, 2014). The idea that this connection is non–linear, and that changes in credit conditions have different implications depending on

[2] The literature on the transmission of monetary policy is too vast to be surveyed here, so we deliberately focus on the contributions that are most directly related to our work.

the state of the economy, has clearly gained attention and credibility after the 2008 financial crisis. Mendoza (2010), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014) develop macroeconomic models where financial shocks are amplified in periods of financial distress, when agents are credit-constrained and thus essentially prevented from fully smoothing consumption. Empirical support for this mechanism is provided by McCallum (1991), Balke (2013) and more recently by Guerrieri and Iacoviello (2013), Alessandri and Mumtaz (2014) and Hubrich and Tetlow (2015), which show that the transmission of various macroeconomic and financial shocks is amplified when financial markets are in turmoil and the economy is close to its borrowing limit. This provides one possible justification for the asymmetry mentioned by Stein (2014): increases in bond spreads may have a larger impact on economic activity because they push firms closer to their borrowing constraints. The example developed in Section 2.2 shows in what way an asymmetry of this type can create a trade-off for monetary authorities and change their optimal response to a generic business cycle shock. In essence, the reason is that in a nonlinear world a temporary compression in credit spreads has two distinct effects on the future distribution of output: it raises its expected value (for the usual reasons) but it also increases its variance, because the reversal of the spread towards its equilibrium level will cause an even larger output drop at some unknown point in the future. In this situation policy makers may well decide to be relatively more passive and accept a lower expected output level for the sake of (keeping the spreads at their equilibrium level and) reducing volatility.

When dealing with the interactions between asset prices and economic activity one should of course think carefully about causality. In a reduced–form sense, the stylized fact that the comovement between credit spreads and economic activity is stronger in recessions than in booms seems generally plausible, and certainly consistent with the history of the last decade. This however does not imply that adverse credit shocks cause large(r) output fluctuations. A reduced-form asymmetry can arise simply because investors respond more strongly to negative news on the macroeconomic outlook. Veronesi (1999) presents a model of investment under uncertainty where equity prices systematically overreact to bad news in good times and underreact to good news in bad times. Beber and Brandt (2010) document that in bond markets contrarian news generally have a stronger impact, and the combination of "bad news in good times" has the largest impact on yields. This is consistent with the asymmetric nature of debt contracts, that is such that negative news are more likely to alter investors' payoffs than positive news, which by and large leave them unchanged. This type of nonlinearity does not create macroeconomic risks and does not cause any troubles to monetary authorities, so disentangling it from the causal asymmetry that underpins the dark side argument is critical. Our strategy to move from predictive regressions to (variously identified) structural models is motivated precisely by this objective.

2.2 Mean-variance trade–off in a two–period economy

To see why an asymmetric link between credit and the economy could change monetary policy choices, consider an economy that lasts two periods ($t = 1, 2$) and that is fully characterized by two equations describing respectively the output gap y and the credit spread s:[3]

$$\begin{aligned} y_t &= \gamma \Delta s_t + \xi \Delta s_t I_{\Delta s_t > 0} + e_t \\ s_t &= \rho s_{t-1} + i_t \end{aligned}$$

The output gap is affected by a random disturbance e_t and by the variation in credit spreads relative to the previous period. The impact of rising spreads on the output gap is negative ($\gamma < 0$) and potentially nonlinear ($\xi \leq 0$): the $\xi < 0$ case introduces the main asymmetry studied in this paper (though in the empirical analysis we also consider the possibility of a nonlinearity in the spread equation itself). The spread follows a simple autoregressive process with persistence $\rho > 0$, and it is affected by the monetary policy rate chosen by the central bank, i_t.[4] This provides the simplest possible set up where (i) monetary policy works through credit markets, as in Gertler and Karadi (2014); (ii) its effects are temporary; and (iii) the central bank may have to take into account that the economy adjusts non-linearly to a tightening in credit conditions. The set up incorporates a number of extreme assumptions (here monetary policy *only* works through credit markets, the pass-through from the policy rate to the spread is complete, and spreads are not hit by additional shocks). These are useful to simplify the central bank's problem and render the trade-off particularly transparent and have no substantive implications for the analysis, which is of course purely qualitative. A monetary stimulus $i_t < 0$ can raise the output gap today by temporarily lowering the spread but it also sows the seeds for the occurrence of a negative gap tomorrow, when the spread reverts back towards its equilibrium level. Consider an economy that starts off from an equilibrium situation where $y_0 = s_0 = 0$. At time 1 an exogenous shock e_1 takes place, the central bank (CB) observes it and decides whether and how to accommodate it by manipulating i_1. No actions and no further shocks take place at time 2. Conditional on the shock e_1, the output gaps at $t = 1$ and 2 are a known function of the policy response:

$$\begin{aligned} y_1 &= \gamma i_1 + \xi i_1 I_{i_1 > 0} + e_1 \\ y_2 &= -(1-\rho) i_1 \left(\gamma + \xi I_{i_1 < 0}\right) \end{aligned}$$

[3]The example is clearly purely illustrative; further details on the derivations can be found in the Appendix to the paper.

[4]We assume without loss of generality that the equilibrium level of the spread is zero; s_t can equivalently be interpreted as the (zero-mean) excess premium relative to some arbitrary equilibrium level.

In this world the policy instrument always moves in an opposite direction to the shock, so that the CB chooses to loosen (tighten) if and only if the initial shock is negative (positive). We can thus focus on the case of a recession $e_1 < 0$ that creates an incentive for the CB to implement some monetary stimulus, and study how the optimal size of such a stimulus is affected by risk preferences and nonlinearity. The loss function of a **risk-neutral** (RN) **central bank** is simply the average output gap over the two periods, that is $\ell^{RN}(e,i) = y_1 + \beta y_2$ where β is the CB's discount factor. By replacing y_1 and y_2 and setting $\ell^{RN}(e,i) = 0$, we obtain the optimal risk-neutral choice:

$$i^{RN} = -\frac{1}{\gamma}\left[\frac{1}{1-\beta(1-\rho)\left(1+\frac{\xi}{\gamma}\right)}\right] e \equiv -\frac{\kappa^{RN}(\xi)}{\gamma} e$$

Since $\kappa^{RN} > 0$ and $\gamma < 0$, the policy response has the same sign as the shock, so that, as anticipated above, interest rates fall after a recessionary shock.[5] A myopic or impatient CB fully accomodates the shock: if $\beta = 0$, then $\kappa(\xi) = 1$ and $i = -e/\gamma \equiv i^{FA}$. In this case the CB chooses to keep the time-1 output gap constant at zero: the future gap will be negative, but the CB does not care about it. Full accommodation can also be seen to be optimal if the spread is a random walk, as $\rho = 1$ again implies $\kappa = 1$. If there is no mean-reversion, the shock can be fully neutralized without paying any costs at $t = 2$. More generally, however, the CB *overreacts* to the shock:

Result (1) A risk-neutral CB responds aggressively to the shock: ($\beta \neq 0$, $\rho < 1$) imply $\kappa^{RN}(\xi) > 1$ and thus $i^{RN} < i^{FA}$. Furthermore, the policy response is increasing in the absolute magnitude of the nonlinearity, i.e. decreasing in ξ: $\partial\kappa^{RN}(\xi)/\partial\xi < 0$.

(see Appendix for details). Knowing that the stimulus comes at the cost of a future contraction, a risk-neutral CB simply engineers a positive gap today that just compensates for the (discounted) negative gap that will materialize tomorrow. The existence of a nonlinearity does not change the nature of this problem: it simply makes the CB more aggressive (provided of course the condition in footnote 6 continues to hold). This behavior creates of course a lot of volatility in y – effectively a boom followed by a recession – but by construction the CB is not concerned about it. A **risk-averse (RA) central bank** aims instead to minimize the variance of the output gap around its zero target. The loss function is given in this case by $\ell^{RA}(e,i) = y_1^2 + \beta y_2^2$. Setting $\partial\ell^{RA}(e,i)/\partial i = 0$ gives the following unique solution:

$$i^{RA} = -\frac{1}{\gamma}\left[\frac{1}{1+\beta(1-\rho)^2\left(1+\frac{\xi}{\gamma}\right)^2}\right] e \equiv -\frac{\kappa^{RA}(\xi)}{\gamma} e$$

[5] We assume throughout that $\beta(1-\rho)\left(1+\xi/\gamma\right) < 1$ so that the problem is well-behaved.

(see again the annex for details). For a myopic central bank, or one that faces random-walk spreads, $\kappa^{RA}(\xi) = 1 = \kappa^{RN}(\xi)$, so the solution is again full accommodation, $i^{FA} = -e/\gamma$. In this case, however, if we move away from those extremes we find that the CB accommodates the shock only in part:

Result (2) A risk-averse CB responds mildly to the shock: ($\beta \neq 0$, $\rho < 1$) imply $\kappa^{RA}(\xi) < 1$ and thus $i^{RA} > i^{FA}$. Furthermore, the policy response is decreasing in the absolute magnitude of the nonlinearity, i.e. increasing in ξ: $\partial\kappa^{RA}(\xi)/\partial\xi > 0$.

Note first that $\kappa^{RA}(0) = (1+\beta(1-\rho)^2)^{-1} < 1$. Even in a linear world ($\xi = 0$) mean-reverting credit spreads create a cost in terms of volatility that a risk-averse CB naturally takes into account when taking its decision. The mean-variance trade-off is such that, in general, the CB accepts a negative average gap for the sake of keeping volatility under control. Furthermore, the shape of the trade-off is a function of the nonlinearity. The larger is ξ in absolute terms (i.e. the lower is $\xi < 0$), the larger is the cost in terms of variance that must be paid to stabilise today's output gap, and the lower is $\kappa^{RA}(\xi)$.

The two messages delivered by this example can be summarised in the following terms. First, mean reversion in credit spreads creates by itself a mean-variance trade-off that makes a risk-averse central bank more cautious in tackling negative economic shocks. A full accommodation of the shock is generally suboptimal for a risk-averse authority. Second, the terms of the trade-off, and the optimal degree of accomodation, depend on the structure of the economy. The CB's incentive to counter recessionary shocks is weaker if a reversal in spreads has a stronger impact on the economy than their initial fall. This provides an intuitive formalization of Stein's (2014) "dark side" argument.

3 Data

We focus on the United States and use the corporate bond spreads and the excess bond premium calculated by (Gilchrist and Zakrajsek, 2012), GZ henceforth, as our main proxy of credit market conditions.[6] GZ use data on corporate bonds traded in the secondary markets to construct prices of *risk-free* securities whose maturities match exactly those of the underlying corporate bonds. This is achieved by simply discounting the cash flows attached to these bonds by the risk-free rates implied in the yield curve at the corresponding maturity. The difference between the yields on the risky corporate bonds and those on the synthetic risk-free securities is an exact measure of the cost faced by each company in excess of the risk-free rate for the maturity at which the bond was issued. Using regression analysis GZ further split

[6] In Section 7 we test the robustness of our results to alternative financial indicators and in the Annex we replicate the analysis for the euro zone and its largest countries.

this firm/bond specific credit spread into two orthogonal components. The first one is the component that can be predicted on the basis of (i) a firm specific measure of expected default and (ii) a set of macroeconomic factors capturing the interest rates term structure, while the second one (the Excess Bond Premium', or EBP) is a residual that measures the excess return investors expect to earn controlling for credit risk. A simple cross-sectional average of these two variables then provides economy-wide measures of expected credit spread and EBP.[7]

From our perspective these indicators have two important advantages. First, they are theoretically appealing, as they do not suffer from the maturity mismatch that plagues commonly used measures like the difference between yields on BAA bonds and a given benchmark risk-free rate. Also notice that, by not confounding risk premia with term premia, they embody more accurately the risk-taking effect prompted my monetary policy. Second, the spread (and particularly EBP) has been found to have significant predictive power over future economic activity. By using them we can test for non-linearities in a set-up where we are fairly confident of a baseline (linear) effect going from current financial conditions to future economic activity.[8]

The expected spread component and EBP are displayed in Figure 1, together with a plain BAA-over-AAA bond spread calculated by Moody's. All measures present (albeit to a different extent) a cyclical profile and a remarkable increase at the onset of the 2008 financial crisis.

In terms of economic activity indicators we rely on a set of standard measures and analyze the industrial production index, non farm payroll employment and the unemployment rate.

4 Nonlinear predictive regressions

We first study the relation between bond spreads and economic activity through a set of reduced-form predictive regressions that take the following form:

$$\nabla^h Y_{t+h} = a(L)\Delta Y_t + \beta_2 term_t + \beta_3 realr_t + \beta_3 \hat{S_t^{GZ}} + \beta_4 EBP_t + \beta_5 EBP_t^+ + \epsilon_{t+h}$$

where the dependent variable $\nabla^h Y_{t+h}$ is the percentage change (cumulated) between t and $t+h$ of economic activity, the term $a(L)\Delta Y_t$ is a distributed lag of the percentage change of the dependent variable, $term_t$ is the term spread, defined as the difference between the three-month constant-maturity Treasury yield and the ten-year constant-maturity yield and $realr_t$ is the short term real interest rate. The term $\hat{S_t^{GZ}}$ is the predicted GZ spread, i.e. the fraction of spreads that is attributable to the expected default component (see Gilchrist and Zakrajsek, 2012, for details), and EBP_t is the Excess Bond Premium. In this regression we allow for this

[7] Analogous measures have been constructed for the euro area, Germany, France and Italy, by Gilchrist and Mojon (2014), who do not however provide a decomposition of the spreads into a predictable and an unpredictable component.

[8] A third advantage, which we exploit in the extensions that look at the euro area, is the cross-country comparability of the spreads calculated by GZ and Gilchrist and Mojon (2014).

last variable, the EBP, to have a potentially asymmetric effect on economic activity through a *local peak* transformation (the term EBP_t^+) that isolates positive changes of the spread and sets to zero (i) decreases and (ii) mild/temporary increases. More formally, for the generic variable x_t, the local peak function is defined as follows:

$$x_t^+(h) = x_t I[x_t > max(x_{t-1}, x_{t-2}, x_{t-3}, ..., x_{t-h})]$$

where $x_t^+(h)$ equals 0 if x_t is not a peak over the past h periods, x_t otherwise. By introducing EBP_t^+ in the regressions we can capture shifts in the correlation between spreads and output that take place when EBP_t reaches a local maximum. [9] Note the maximum can be reached either because the spread rises consistently for h periods and/or because a large shock suddenly pushes it above its recent historical values. The constant h determines how persistent the shock to the EBP has to be for this additional regressor to be active, i.e. different from zero. With $h = 1$ any increase in EBP qualifies as a local peak, so that $EBP_t^+ = EBP_t$ whenever $EBP_t > EBP_{t-1}$ (and $EBP_t^+ = 0$ otherwise). As h increases, non-zero values of EBP_t^+ become progressively less frequent, capturing only large/persistent movements in spreads. The economic rationale for using this transformation is that small, temporary shocks to credit conditions can be more easily smoothed out by firms through profit margins, while large or persistent changes in the cost of credit are more likely to affect investment and output. In this setup, a test for asymmetric effects is that the coefficient β_5, associated with EBP_t^+ in the above regression, is significantly different from zero. This approach to testing for asymmetries has a long tradition in applied econometrics, having been extensively used for instance to test for the asymmetric effects of oil price shocks on economic activity and inflation, see e.g. Borenstein *et al.* (1997) and Meyler (2009) for a review. Its methodological limitations are discussed by Kilian and Vigfusson (2013).[10]

The results obtained from these predictive models are reported in Table 1. The table collects a range of specifications that differ along three dimensions: (i) the lags to be considered when computing local peaks for the credit spread (from 12 to 36); (ii) the forecasting horizon (from 6 to 18 months ahead); and (iii) the measure of economic activity used as forecasting target (Employment, Industrial Production, Unemployment rate). Readers that are familiar with Gilchrist and Zakrajsek (2012) will recognize that our regressions simply augment their basic

[9] For a visual impression of what the $EBP+$ transformation looks like, see the top panel of Figure **??**. This is discussed in greater detail in Section 7.4.

[10] Kilian and Vigfusson (2013) show that in the presence of censored variables (like EBP_t^+) reduced-form regression coefficients can give a very distorted view of whether or not shocks are transmitted asymmetrically, and that, since the IRFs are a complex nonlinear function of the parameters, the bias can go either way (small coefficients on the asymmetric terms can coexist with significant dynamic asymmetries, and large coefficients do not necessarily imply that such an asymmetry exists). The structural multivariate models introduced in Section 5 clearly are not subject to this problem.

setup with the local peak variables EBP_t^+. Hence, it does not come as a surprise that EPB turns out to be a significant predictor of economic activity. This result is robust to different forecast horizons and it emerges for all the measures of real activity we consider. Furthermore, all the coefficients in the regressions display the expected sign, so that an increase in the real rate of interest, a rise in credit spreads (either in its predicted component or in EBP) and a flattening of the yield curve are associated to a future economic contraction.

The key object of interest is of course EBP_t^+. In the case of industrial production, we find its coefficient to be highly significant for all horizons and for all specifications of the local peak function. For employment and unemployment the coefficient is again significant as long as one focuses on large values of h (i.e. large and persistent increases in credit spreads) and on forecasting horizons of 12 months or more. These regression results confirm and extend the evidence presented in Stein (2014), where a similar predictive exercise is conducted on a different sample and focusing on GDP growth. All in all, the balance of evidence clearly supports the notion that credit spreads move more ahead of negative cyclical phases. As we noted in section 2, this finding might arise because financial markets anticipate recessions or because negative financial shocks have a stronger effect on economic activity. In the next two sections we turn to structural analysis to discriminate between these two possibilities.

5 Multivariate structural models

Are the correlations documented in the previous section a symptom that credit markets have a nonlinear impact on economic activity? In order to answer this question one needs to resort to a multivariate model that captures the feedbacks between the two and permits a structural identification of the primitive shocks of interest. To that end, we augment an ordinary VAR with local peaks of the endogenous variables. More formally, we work with the following system of equations:

$$y_{t+h} = a^h + \sum_{i=0}^{p-1} B_i^h y_{t-i} + \Theta^h L y_t^+ + v_{t+h} \tag{1}$$

where a set of endogenous variables y_t are regressed onto themselves lagged from h to $h+p$ periods and on their local peak transformations y_t^+. The matrix L is a selection matrix with all zeros, except for the column corresponding to the position of the variable that enters asymmetrically.[11] The *local projections* method of Jorda (2005) can be promptly used to calculate generic impulse-response functions in this context. In particular, as we show in

[11] For example, in a bivariate model allowing for asymmetric effects of the second variable in the first equation we have L $= \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$, so that $Ly_t^+ = \begin{pmatrix} y_{2,t}^+ \\ 0 \end{pmatrix}$

Appendix C, in this case the IRF can be computed directly as:

$$IRF(h,t) = B_0^h d_i + \Theta^h L \widetilde{y}_t \tag{2}$$

where

$$\widetilde{y}_t = [(y_t + d_i)^+ - y_t^+]$$

and d_i is a shock to the i^{th} variable in the system. Such a shock can be given a structural interpretation on the basis of identifying restrictions, akin to the ones used in the structural VAR literature. Crucially, notice that in the first term in $\widetilde{y}_t$ the net increase function is applied to the sum of the historical value of y_t at time t and the shocks vector d_i. This makes the IRF dependent on the *history* of the variable and on both the *sign* and the *size* of the shock. This feature makes more explicit the nonlinearity of the effect of a shock in a system in which there are censored variables, further motivating the use of multivariate models to complement our baseline regression analysis. In our baseline specification the y_t vector includes economic activity (measured again by industrial production, employment or the unemployment rate), EBP, term spread, (log) CPI index and the interest rate on one-year government bonds. We later extend the analysis to include alternative credit indicators and measures of volatility and sentiment. By altering the definition of L, and by adopting a suitable identification strategy for the primitive shocks, we can use this framework to separately examine the two possibilities laid out in the introduction to the paper.[12]

The first and most important possibility, which we discuss in Section 6.1, is that output responds asymmetrically to variations in credit spreads (conjecture (i)). In this case, the L matrix has an entry equal to 1 in the position that corresponds to the spread term in the output equation. This nonlinearity could be triggered in principle by any variation in spreads that does not merely reflect an expected change in the business cycle. We identify such variations in two alternative ways. We focus primarily on variations in spreads that are directly caused by monetary decisions, for two reasons: first, these are clearly the most relevant for the dark side mechanism; second, they can be reliably identified using high-frequency data and external instruments (Gertler and Karadi (2015); see also Stock and Watson (2012) and Mertens and Ravn (2013)). The methodology consists of three steps. First, we estimate the vector of the reduced form residuals from the OLS regressions of the multivariate model, in our case obtained by local projections. Second, we instrument the residual of the interest rate equation (for which we use the one-year government bond rate) with the monetary surprise, using 1 month fed fund future rates, 3 month fed fund future rates and Euro/Dollar deposits 2, 3, and

[12] Testing these mechanisms one at a time is both convenient and, in our view, more informative. Introducing more than one nonlinearity at the same time would complicate the estimation of the model and the interpretation of the results and probably weaken the inference.

4 months ahead. Third, we estimate the contemporaneous response of the remaining variables to the fitted values obtained in the first stage. This identification strategy is attractive in our context because, unlike recursive identification, it deals well with simultaneity problems (monetary conditions might also respond to financial developments within the month) and with the fast response of financial markets to central banks' decisions (an issue that is likely to be particularly important for the unconventional monetary interventions undertaken by the Fed after the Global Financial Crisis). The approach has a third important advantage: by looking at the variation in one-year bond rates following a monetary surprise we can capture at least in part the impact of policy shocks on the term structure of interest rates, thus accounting for forward guidance.[13]

Although monetary surprises are central to the dark side argument, their impact on credit spreads might conceivably be too feeble to identify (potential) nonlinearities in the data. As an alternative, we thus also look at variations in credit spreads that are only orthogonalized with respect to the state of the business cycle. In this case we use a simple exclusion restriction that rules out a contemporaneous response of economic activity to unpredictable changes in EBP, thus classifying as "spread shocks" all variations in EBP that have a causal impact on the real economy rather than being an endogenous response to business cycle conditions. This set effectively contains linear combinations of all the structural shocks that do not affect economic activity in the month when they materialize (including term spread, monetary policy or credit supply shocks stemming from changes in risk preferences). The underlying variations in spreads are by construction larger and more frequent than those stemming exclusively from monetary shocks.[14]Hence, this identification strategy takes us a step away from the theoretical argument but it increases our power to detect a non-linearity in the relation between spreads and economic activity.

The second possibility for a policy trade-off to arise is if credit spreads respond asymmetrically to monetary shocks (conjecture (ii) in the introduction). If the linkage between credit markets and the rest of the economy is in itself linear, but the way markets respond to monetary decisions is not, central banks face again a situation where temporary stimulus creates a cost in terms of macroeconomic variance in the longer term. This mechanism is conceptually different from the previous one, but it can be easily accommodated within our set-up. We simply adjust the L matrix so that a shock to the policy measure translates into effects on the credit spread indicator, i.e. the EBP. The only source of shocks of interest in this case is monetary policy,

[13]The one-year bond rate is our preferred policy measure because it strikes a good balance between (i) being sufficiently sensitive to monetary surprises (so that the instruments are valid), and (ii) accounting for term structure (i.e. forward guidance) effects. See Gertler and Karadi (2015) for details.

[14]Gilchrist and Zakrajsek (2012) use a recursively-identified linear VAR and find that almost 75% of the variance of EBP is explained by exogenous credit shocks; Furlanetto *et al.* (2014) employ VARs with sign restrictions and conclude that uncertainty and housing are important drivers of EBP.

for which we can rely on the external instrument identification strategy sketched above. The results of this analysis are discussed in Section 6.2.

6 The implications of credit and monetary policy shocks

6.1 Does output respond asymmetrically to credit spreads?

The first proposition we examine is whether an increase in spreads triggered by an unexpected monetary tightening – identified as in Gertler and Karadi (2015) – causes a disproportionately large response in economic activity. We consider a parsimonious specification of the model that includes economic activity (variously defined), CPI, short term rates, term spread and EBP. The local peaks in EBP are defined as in the regressions discussed in Section 4, and they are calculated based on the behavior of the spreads over the 12 months prior to the shock ($h = 12$).[15]

The responses generated by the model are displayed in Figure 2. The plots are organized as follows. Each row refers to a different measure of economic activity, i.e., moving down from the top, employment, industrial production or the unemployment rate. From left to right, responses to shocks of increasing size are plotted, from 25 to 100 basis points. Within each plot, the black line represents the estimated median responses to a restrictive monetary shock (i.e. an increase in the one–year government bond rate) and the red line represents the response to an expansionary shock of the same size. The latter are multiplied by minus one to facilitate the visual comparison of the effects of positive and negative shocks. In all cases the median estimated response is accompanied by 68% and 90% confidence intervals (displayed respectively as dark and light grey areas). A positive 25 basis point shock produces a contraction in employment and industrial production and an increase in the unemployment rate. These effects are persistent and highly significant. However, the IRFs to a positive and a negative shock overlap almost perfectly: there is no evidence that contractionary shocks have a larger impact on economic activity. One could suspect that this result is caused by the modest size of the shock, but it turns out that this is not the case. If we condition on shocks of 50 or 100 basis points (column 2 and 3), the estimated responses naturally become larger but the equivalence of positive and (inverted) negative shocks is confirmed for all forecasting horizons.

As a next step, we check whether this conclusion holds when we broaden the picture, moving from monetary shocks to a more encompassing class of "credit shocks". As we note in Section 5, by considering a more volatile source of variations in credit spreads we might gain power in identifying a potential nonlinearity in the linkage between credit markets and the real economy. We use the same model as above, but in this case we focus on EBP shocks and we rely on

[15] As we show in Section 7, the results obtained in this set-up are robust to various modifications and extensions of the benchmark specification.

a recursive identification scheme: we simply assume that economic activity responds with a lag to an exogenous variation in EBP (an assumption that is fairly standard in the literature, and seem fairly plausible with monthly data). Figure 3 shows the effects of a shock to EBP on output. The figure has the same structure as the previous one. In this case the black line represents the median response to a positive shock, i.e. an increase in tensions on credit markets captured by a rise in EBP, while the red line represents the response to a negative shock, i.e. a fall in EBP. Two considerations are in order. First, although in this case the contemporaneous responses are zero by construction given our identification assumptions, the peak responses are somewhat larger than those shown in figure 2. This suggests that some of the primitive shocks captured in this exercise (variations in risk preferences being an interesting candidate) are relatively more powerful than the monetary policy shocks we examined earlier.[16] Second, in this case the size of the shock plays some role in driving the asymmetry. The overlap between positive and negative shocks is again perfect for 25bps shocks (first column), but in the case of 100bps shocks the median responses tend to be larger when EBP rises (third column). The statistical significance of these differences is however very low. Our interpretation of the results is that the data does contain episodes where spikes in EBP caused relatively large economic contractions, but these are (a) too rare to generate a significant nonlinearity, and (b) in any case unrelated to monetary surprises.

6.2 Do credit spreads respond asymmetrically to monetary shocks?

There is another situation where a trade-off for monetary policy may arise: that is the case where, although the linkage between credit markets and economic activity is in itself linear, the reaction by credit markets to monetary surprises is not. This configures a scenario where the "risk off" phase triggered by a negative (i.e. contractionary) monetary shock is more dramatic or more abrupt that the "risk on" phase; in other words, investors buy risk gradually but tend to offload it quickly when monetary conditions tighten. Such an asymmetry could be generated by the presence of levered investors subject to funding constraints (Brunnermeier and Sannikov, 2014). Its empirical relevance has been documented for currency markets, where the conventional wisdom that "exchange rates go up by the stairs and down in the elevator" is supported by formal econometric evidence (Brunnermeier *et al.*, 2009). Our data and set up allow us to test its relevance in the case of corporate bond markets.

In Figure 4 we show the dynamic response of EBP to a monetary policy shock identified by means of external instruments. As in the previous case, the three columns report the responses associated to shocks of different size. The rows refer instead to specifications based on our three measures of economic activity. The dynamics in EBP are clearly very similar across specifications. The behavior of the spread is consistent with that documented by Gertler and

[16] This comparison is a sensible one because we are comparing variations in EBP of the same absolute size (all shocks are defined in terms of basis points rather than standard deviations)

Karadi (2015): EBP increases significantly on impact and remains positive for over a year after the shock. This result adds to the existing evidence in support of a market-based risk-taking channel for monetary policy in the US. Our model also allows us to make statements concerning the way markets adjust to shocks of different size and direction. In short, neither of the two dimensions matters. Moving across the columns of 4, one clearly sees that the response by EBP is linear in the size of the monetary shock, irrespective of which economic activity indicator is used in the model. Furthermore, red and gray bands overlap almost perfectly, implying that the response of EBP to contractionary and expansionary shocks of a given size are nearly identical. Taken together, our results thus exclude both (a) the possibility that credit conditions move more in response to a tightening by the Fed, and (b) the possibility that the market response is identical but its impact on the real implications is higher when spreads move upwards.

7 Robustness

In this Section we extend our baseline analysis in five dimensions, considering in turn: the role of economic uncertainty in the transmission of the shocks; broader financial conditions indicators; the nature of the transmission during recessionary episodes; alternative indicators of non–linearities; a recursive identification for monetary shocks. The model specifications used in this extensions are summarized for reference in Table 2.[17]

7.1 Accounting for uncertainty and consumer confidence

In the aftermath of the Global Financial crisis there has been a growing interest in evaluating the effects of uncertainty on the business cycle (see the survey in Bloom, 2014; Caggiano *et al.*, 2014, among others, analyze the implications of different states of the economy for the transmission of uncertainty shocks). The literature shows that a higher degree of uncertainty can not only *directly* affect economic activity and inflation, but it may also interact with the transmission of financial shocks to the real sector. In particular, Caldara *et al.* (2015) recommend to simultaneously identify uncertainty and financial shocks in order to properly disentangle their relevance as drivers of economic fluctuations. Although we are not interested in identifying the effects of uncertainty *per se*, the interaction between uncertainty and credit conditions might play a role in our case too. Hence, in models 4 , 8 and 12 of Table 2 we include uncertainty among the controls. We capture it in two ways. The first one is the measure recently proposed by Jurado *et al.* (2015), who use a data–rich environment approach to estimate a measure of *macroeconomic* uncertainty, showing that this outperforms comparable indicators of volatility used by the literature in both forecasting and structural models. The

[17] In the robustness analysis we focus for brevity on monetary policy shocks only. The empirical findings related to credit (EBP) shocks are also robust along these dimensions (the results are available upon request).

second one is consumer confidence measured by the Michigan Index of consumer confidence, a widely-used series in the literature on expectations, news and confidence shocks (Barsky and Sims, 2011, 2012). The forward–looking nature of this indicator can be particularly useful in multivariate models, as it adds non–trivial information which would otherwise be unaccessible to the econometrician.[18] Results are presented in Figures 5, 6 and 7, each for a different definition of non–linear indicator (see Section 7.4 for more details). In spite of some increase in the distance between the median estimates of iRFs to expansionary and contractionary monetary policy shocks, the confidence bands do overlap, thus validating the main conclusion of the baseline specification: no evidence of asymmetries is visible. Uncertainty and consumer confidence do not seem to alter the transmission of monetary policy through credit spreads, and do not change the general conclusions of our analysis.

7.2 Alternative indicators of financial distress

Up to this point, we have focused on the EBP as the variable through which the policy trade–off described by Stein (2014) may arises. This choice is motivated not only because of the willingness to resemble as close as possible to the equation estimated by Stein (2014), but also because of the relevance of credit markets – in particular credit spreads – in explaining the crisis of 2007–09. However, despite this evidence, one may argue that other financial variables may trigger some non–linear relation with economic activity (see, for example, Adrian *et al.*, 2015; Hubrich and Tetlow, 2015). To evaluate this possibility, we replace the EBP with the Chicago Financial Condition Index, which measures periods of financial stress by extracting a synthetic indicator from a number of financial variables, providing a comprehensive update on U.S. financial conditions in money markets, debt and equity markets and the traditional and shadow banking systems. Results are reported in Figures 12–14, respectively showing the dynamic effects of monetary policy shocks identified by external instruments and Choleski decomposition (see Section 7.5). In both cases, the effects of monetary easing and tightening are not statistically distinguishable from each other. Thus, we tend to exclude the possibility of money or equity activating the dark side of monetary policy, inducing asymmetric effects on economic activity.

7.3 The role of recessions

There is a growing body of papers evaluating the effects of monetary policy in different phases of the business cycle. For example, Santoro *et al.* (2014) find that monetary policy exerts

[18]Volatility and confidence are introduced jointly into the model; the findings do not change if they are used one at a time.

asymmetric effects on output over contractions and expansions in economic activity. They explain this evidence with higher responsiveness of output to interest rate changes, as well as a flatter aggregate supply schedule faced by the central bank during contractions. Also, Tenreyro and Thwaites (2016) estimate the impulse response of a number of US macro series to the monetary policy shocks, allowing the response to vary over the state of the business cycle, finding that contractionary policy shocks have more powerful effects than expansionary shocks. Although we do not develop here a formal state–dependent model, our framework allows us to condition the estimate of our IRFs over periods of recessions, instead of taking into account the whole history of economic activity. A recession is defined as a period in which the y-o-y growth rate of employment, industrial production or unemployment rate is negative (positive for the latter). Remember that the IRFs depend not only on the size and on the sign of the shock, as evident from the results presented so far, but also on the history of the variable that is being shocked, as explained in section 5. While the results shown in Figure 2 are obtained conditioning on the mean value of the endogenous variables, it could be interesting to look at IRFs obtained conditional on a particular state of the economy. Of particular interest, for example, are the periods in which economic activity has persistently fallen. Restricting the analysis to these subsamples can shed some light on the issue of whether asymmetric effects are more evident in bad, rather than in normal, times as suggested, for instance, by Tenreyro and Thwaites (2016). In this case, too, no evidence of asymmetries is detected (see Figure 8, when using the local peak indicator for the term EBP^+, whereas Figures 10–11 for alternative definitions of non–linear indicators (see also section 7.4).

7.4 Alternative definitions of non–linearities

Our analysis relies on the identification of "exceptional" increases in bond spreads, which is clearly arbitrary to some extent. With respect to the baseline definition of EBP^+ employed thus far, two alternative options can be considered: (i) the horizon over which the net increase is computed and (ii) the type of non–linear function underlying the calculation. As for the first dimension, we compute our local peaks over a period of 24 and 36 months instead of 12 as in the baseline case. The results, not reported here in order to save space, are qualitatively and quantitatively unaffected. Moving to alternative indicators of non linearities, we propose and use two formulations. The first one, labeled $S - diff$, is defined as $x_t^+(j) = (x_t - x_{t-h})I[x_t - x_{t-h} > 0]$. Here the net increase is activated every time the change in EBP is positive over the last $j = t - h$ periods (where, again, we choose h=12 as baseline). The second one, labeled $S - plus$, is defined as $x_t^+ = x_t I[x_t > 0]$: this restricts the focus to occurrence of positive excess bond premia. The indicators are displayed in Figure 9. The first panel shows the local peak function with horizon 12 months used throughout Section 4 and 5; the other two panels refer respectively to $S - diff$ and $S - plus$. In all three cases, the row EBP series is represented by the dotted blue line.

Although when using the $S - plus$ definition there is some weak non–linear effect, this is never statistically significant. We conclude that the main message of our empirical analysis is robust to different definitions of non-linearity in EBP. [19]

7.5 Recursive identification of monetary policy shocks

As a final check, we run our structural models identifying monetary policy shocks by means of a recursive (Cholesky) scheme, conventionally used in macroeconomic literature (Gilchrist and Zakrajsek, 2012; Jurado *et al.*, 2015). We plot the results in Figure 13, referring in particular to specification 4 of Table 2, i.e. the one comprising volatility and consumer confidence. Here we observe that, for large shocks only (100bp), contractionary monetary policy shocks seem to exert stronger effects on economic activity than expansionary shocks of equal size. This is particularly visible for industrial production and the unemployment rate. Although the nonlinearity shows up more significantly in this exercise than in our baseline analysis, the evidence remains altogether weak, especially considering that this is the only case in which it is observed. In fact, the emergence of a nonlinearity might in this case be another, indirect proof that recursive identification has serious limitations in this type of problems. The general limitations of this approach are known, particularly when dealing with financial data (Carlstrom *et al.*, 2009; Gertler and Karadi, 2015). In our case, this identification scheme delivers an asymmetry that (i) resembles that uncovered in the reduced-form regressions of Section 4, and (ii) is much stronger than that estimated under the (more reliable) assumptions made in Section 5. This is consistent with the possibility that – like the predictive regressions – the assumed recursive structure essentially fails to disentangle exogenous variations in EBP from the (possibly dominant) cases where spreads rise in anticipation of a contraction in economic activity.

8 Reconciling the evidence from reduced form and structural models

The empirical evidence presented so far has shown that credit spreads predict recessions more accurately than expansions, but that the transmission of monetary policy shocks to the real economy through credit spreads is overall linear. It then remains to be explained why the results obtained from reduced form models differ from those stemming from structural models.

A first line of explanation is purely econometric. In a sense, the difference between Impulse Response Functions to identified structural shocks and regression coefficients in predictive

[19] The whole set of graphs obtained using the two alternative indicators is available upon request.

regressions is similar to the difference between the estimates obtained on the basis of Instrumental Variables (IV) methods and those obtained with Ordinary Least Squares (OLS). As IV estimates correct for possible endogeneity biases, they are likely to differ (not always in a predictable direction) from those obtained via OLS.

This of course, does not explain the asymmetric predictive ability of credit spreads on future economic activity. To understand this result an economic, rather than an econometric, argument must be put forward. As we have discussed in the Introduction a reduced-form asymmetry can arise simply because investors respond more strongly to negative news on the macroeconomic outlook. A closer look at this statement reveals that three conditons are needed for this to be true. First, there must be macroeconomic shocks that (controlling for a number of covariates like those used in our predictive regression framework) anticipate future economic activity. Second, these shocks must have an asymmetric impact on credit spreads. Third they must be orthogonal to the monetary policy shock on which we have based the structural analysis presented in Section 6.

In this Section we provide some evidence that this economic explanation can indeed be substantiated in our setup and in our data sample. To this end we resort to a measure of macroeconomic news. For every month t, this is defined as the difference between the unemployment rate update published in month t and the median unemployment expectation held by market participants the day before the data release.[20]

The financial crisis triggered by the collapse of Lehman Brothers was characterized by a stream of bad news, while during the cyclical upswing that followed the crisis the markets underestimated the pace of recovery of the unemployment rate. This type of macroeconomic ''surprises" are very popular in the asset pricing empirical literature, (see for instance Gürkaynak *et al.*, 2005; Faust *et al.*, 2007; Goldberg and Grisse, 2013) and are known to be significant movers of financial market prices.

We start from the first part of the argument, that is we show that this macroeconomic news has predictive ability over future economic activity over and above the standard set of macroeconomics controls that were used in the predictive regressions in Section XX. To this end we run dynamic regressions of this type:

$$\nabla^h Y_{t+h} = a(L)\Delta Y_t + \Gamma' x_t + \beta U_t^{news} + \epsilon_{t+h} \tag{3}$$

where Y is either the Unemployment rate or Industrial Production or Employment, x_t is a vector of macroeconomic controls (namely term spread, real fund rates and credit spreads) and U_t^{news} is the unemployment rate news. Table 3 reports the t-statistics associated with the coefficient β in the above equation. First, the statistics have the expected sign, that is bad unemployment rate news predict higher unemployment and lower IP and employment 6,

[20] Data on these surprises are taken from Bloomberg.

12 and 18 months ahead. Second, they are all (but one) higher than 1.95 in absolute value, indicating that the estimated coefficients are significantly different from zero.

Second, we need to show that credit spreads react more to bad than to good news. To this end we estimate the following equation:

$$EBP_t = \alpha + \Gamma' z_t + \beta^{bad} U_t^{news} I(U_t^{news} > 0) + \beta^{good} U_t^{news} I(U_t^{news} \leq 0) + u_t \tag{4}$$

where z_t is a vector of macroeconomic controls (namely term spread, real fund rates, predicted GZ spread and lagged unemployment rate). To separate the effects of good and bad unemployment news we inteact the term U_t^{news} with dummy variables that identify periods in which U_t^{news} is, respectively, positive (bad news) and negative (good news). The first two columns in Table 4 show the results obtained from the estimation of equation (3) omitting the vector z_t. The results show that while β^{bad} is significantly different from zero, β^{good} is not, that is, the Excess Bond Premium tightens significantly in response to bad macroeconomic news, but is overall unresponsive to good news. The latter two columns show that this result holds when we add macroeconomic controls z_t to this regression.

To close our argument we need to check that indeed the macro news we are considering are orthogonal to Monetary Policy Shocks. We do this by running the following regression

$$U_t^{news} = \alpha + \beta MP_{suprise} + u_t \tag{5}$$

As Table 5 shows, the estimated coefficient β is not different from zero, indicating that two news are indeed orthogonal to each other.

9 Conclusions

Monetary policy exerts a significant influence on market risk premia. If this part of the transmission mechanism is asymmetric, so that credit spreads have a stronger impact on output when they rise than when they decline, monetary authorities may face a delicate trade-off: monetary stimulus might ease credit conditions and close the output gap in the short run, but also increase the risk of a costly reversal in market sentiment in the longer term (Stein, 2014). We first discuss the conditions under which this problem arises, using a simple analytical example to illustrate why the policy trade-off is indeed steeper if the link between credit markets and output is asymmetric. We then exploit the dataset constructed by Gilchrist and Zakrajsek (2012) to develop a thorough econometric investigation of the relation between monetary policy, credit spreads and economic activity in the US. Reduced-form predictive regressions suggest that corporate bond spreads systematically experience a sharp rise ahead of a slowdown in economic activity. Crucially, though, this asymmetry has little to do with monetary policy. Monetary shocks – which we identify adopting the external instrument strategy of Gertler and

Karadi (2015) – do not have an asymmetric impact either on financial markets or on economic activity: on the contrary, bond spreads, industrial production, employment and unemployment all display dynamics that are perfectly symmetric to contractions and expansions in the monetary stance. These results suggest that the asymmetry is best interpreted as a predictive rather than a causal relation, which arises because bond markets tend to rise dramatically in anticipation of a worsening in the macroeconomic outlook. Since this phenomenon does not depend on the monetary stance, central banks should not be overly concerned about their decisions causing spikes in risk premia and unnecessary economic volatility. To the extent that our identification strategy successfully captures the impact of forward guidance, this conclusion directly applies to the current US outlook, and it suggests that the lift–off from the prolonged monetary expansion implemented by the Fed should not come at a cost that is so high as to raise doubts on whether the stimulus was worth undertaking in the first place. A few caveats are in order. Nonlinearities are generally elusive, and it is possible that the asymmetry between credit conditions and output is confined to particular states of the economy – such as those where private debt is excessive, uncertainty is high, or nominal interest rates are constrained by the Zero Lower Bound. A more thorough investigation of these possibilities is left to future research.

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Tables

Table 1: Credit spreads, economic activity and non–linearities: USA

Order of local peak		12			24			36	
Forecast horizon	6	12	18	6	12	18	6	12	18
				Employment					
Term Spread	-0.09	-0.19	-0.31	-0.09	-0.21	-0.30	-0.09	-0.19	-0.31
p-val	**0.03**	**0.06**	**0.01**	**0.04**	**0.01**	**0.01**	**0.04**	**0.06**	**0.02**
Real Fed Funds	0.09	0.14	0.14	0.09	0.14	0.14	0.09	0.15	0.14
p-val	*0.20*	*0.37*	*0.28*	*0.19*	*0.21*	*0.25*	*0.18*	*0.30*	*0.24*
Predicted GZ spread	-0.10	-0.13	-0.21	-0.10	-0.13	-0.20	-0.09	-0.12	-0.20
p-val	*0.11*	*0.33*	*0.21*	*0.11*	*0.25*	*0.18*	*0.13*	*0.32*	*0.20*
EBP	-0.14	-0.17	-0.16	-0.15	-0.18	-0.17	-0.14	-0.17	-0.17
p-val	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
EBP^+	-0.13	-0.20	-0.21	-0.14	-0.23	-0.24	-0.16	-0.25	-0.25
p-val	0.13	0.12	0.11	0.16	**0.02**	**0.01**	0.15	**0.05**	**0.01**
R^2	0.76	0.65	0.56	0.76	0.64	0.56	0.76	0.65	0.56
				Industrial production					
Term Spread	-0.06	-0.11	-0.19	-0.06	-0.11	-0.19	-0.06	-0.11	-0.19
p-val	*0.22*	*0.29*	*0.17*	*0.26*	*0.39*	*0.14*	*0.24*	*0.39*	*0.11*
Real Fed Funds	0.01	0.00	-0.06	0.02	0.01	-0.06	0.02	0.01	-0.06
p-val	0.89	0.97	0.58	0.83	0.93	0.54	0.81	0.92	0.53
Predicted GZ spread	-0.13	-0.16	-0.24	-0.12	-0.16	-0.24	-0.12	-0.16	-0.24
p-val	**0.03**	*0.11*	**0.04**	**0.03**	*0.11*	**0.02**	**0.03**	**0.16**	**0.02**
EBP	-0.20	-0.19	-0.15	-0.21	-0.20	-0.16	-0.21	-0.20	-0.16
p-val	**0.01**	**0.03**	**0.10**	**0.00**	**0.01**	**0.06**	**0.00**	**0.01**	**0.07**
EBP^+	-0.22	-0.29	-0.22	-0.26	-0.33	-0.26	-0.26	-0.34	-0.26
p-val	**0.01**	**0.00**	**0.02**	**0.01**	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**
R^2	0.45	0.35	0.26	0.46	0.36	0.26	0.46	0.36	0.26
				Unemployment rate					
Term Spread	0.12	0.25	0.36	0.12	0.25	0.35	0.12	0.25	0.35
p-val	**0.07**	**0.03**	**0.77**	**0.08**	**0.03**	**0.10**	**0.09**	**0.03**	*0.48*
Real Fed Funds	-0.06	-0.07	-0.02	-0.07	-0.08	-0.03	-0.07	-0.08	-0.03
p-val	*0.63*	*0.76*	*0.99*	*0.62*	*0.74*	*0.96*	*0.61*	*0.70*	*0.97*
Predicted GZ spread	0.10	0.11	0.17	0.09	0.11	0.17	0.09	0.10	0.16
p-val	*0.27*	*0.48*	*0.81*	*0.28*	*0.47*	*0.56*	*0.30*	*0.48*	*0.57*
EBP	0.26	0.24	0.19	0.25	0.24	0.20	0.25	0.24	0.19
p-val	**0.00**	**0.00**	*0.80*	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	*0.25*
EBP^+	0.09	0.23	0.24	0.13	0.29	0.31	0.16	0.32	0.33
p-val	*0.30*	**0.05**	*0.86*	*0.21*	**0.01**	**0.04**	*0.17*	**0.00**	**0.00**
R^2	0.53	0.44	0.38	0.54	0.44	0.39	0.54	0.45	0.39

Notes: Sample is 1973:01 - 2012:12. Dependent variables is $\nabla^h Y_{t+h}$, where Y_t denotes the respective economic activity variable in the subpanel title in month t and h is the forecasting horizon. *Order of local peak* represents the number of periods over which the asymmetric term of the financial variable is computed. Each regressions also include a constant and p lags of the dependent variable (not reported), where p is chosen by the BIC. Entries in the table denote the standardized estimates of the OLS coefficients associated with each financial indicator, whereas italics terms are the p-values computed by means of the Newey–West (1987) correction.

Table 2: Multivariate model, list of specifications.

	History	Nonlinearity	Variables in the model
1	All	Loc. Peaks	Output, EBP, Short Rates, Term Spread, CPI
4	All	Loc. Peaks	Output, EBP, Short Rates, Term Spread, CPI, Michigan, Volatility
5	All	S–Diff	Output, EBP, Short Rates, Term Spread, CPI
8	All	S–Diff	Output, EBP, Short Rates, Term Spread, CPI, Michigan, Volatility
9	All	S–Plus	Output, EBP, Short Rates, Term Spread, CPI
12	All	S–Plus	Output, EBP, Short Rates, Term Spread, CPI, Michigan, Volatility
13	Recessions	Loc. Peaks	Output, EBP, Short Rates, Term Spread, CPI, Michigan, Volatility
14	Recessions	S–Diff	Output, EBP, Short Rates, Term Spread, CPI, Michigan, Volatility
15	Recessions	S–Plus	Output, EBP, Short Rates, Term Spread, CPI, Michigan, Volatility
16	All	Loc. Peaks	Output, CFCI, Short Rates, Term Spread, CPI, Michigan, Volatility

Notes: Under the column *History* we report whether we condition the Impulse Response Functions on the whole history (All) or on Recession period (Recessions). The latter are defined as periods in which output at time t is lower than output a year before. Under the column *Type of nonlinearity* we report the transformation of the measure of financial condition used in the model to account for asymmetries in the transmission of a shock. The options are (i) local peak, defined as $x_t^+(j) = x_t I[x_t > max(x_{t-1}, x_{t-2}, ..., x_{t-j})]$, (ii) S-diff, defined as $x_t^+(j) = (x_t - x_{t-h})I[x_t - x_{t-h} > 0]$, (iii) S-minplus, defined as $x_t^+ = x_t I[x_t > 0]$. Short Rates are the 1 year government bond rates in Gertler and Karadi (2015). In the econometric exercise we instrument the innovations to this rate with the surprise in the three month ahead Fed Funds Futures rate.Since our specification is slightly different from the one adopted by Gertler and Karadi (2015) we have analyzed the robustness of this instrument for the innovation to the 1 year rate. Results, available upon request, confirm that the the three month ahead Fed Funds Futures rate has good power in explaining the residuals of the 1 year government bond. The term spread is the difference between the 10 year government bond rates and the Fed Funds Rates. Michigan is the Michigan Sentiment Index. Volatility is the measure of Uncertainy computed by Jurado, Ludvigson and Ng (2015), see Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. 2015. "Measuring Uncertainty." American Economic Review, 105(3): 1177-1216.

Table 3: PREDICTIVE POWER OF UNEMPLOYMENT NEWS ON ECONOMIC ACTIVITY

Forecast Horizon	6	12	18
Urate	2.91	2.93	2.58
IP	-2.50	-2.26	-1.85
Employment	-3.04	-2.63	-2.19

Notes: The table reports the t-statistics of the coefficients related to U_t^{news} in equation (3).

Table 4: REACTION OF EBP TO BAD AND GOOD UNEMPLOYMENT NEWS

	W/O controls		With controls	
	β	p-val	β	p-val
Bad News	2.01	0.00	1.41	0.03
Good News	-0.45	0.23	-0.41	0.26

Notes: The table reports the t-statistics of the coefficients related to EBP_t in equation (4).

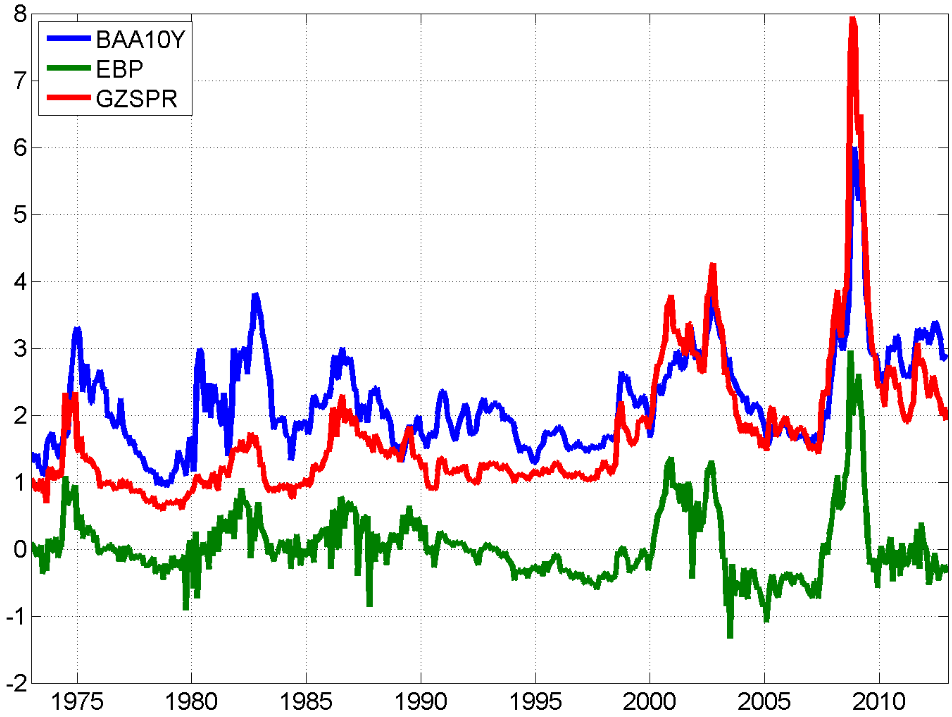
Table 5: UNEMPLOYMENT RATE AND MONETARY POLICY NEWS

	β	p-val
Intercept	-0.03	0.02
Mon Policy News	-0.19	0.25

Notes: The table reports the t-statistics of the coefficients related to U_t^{news} in equation (5).

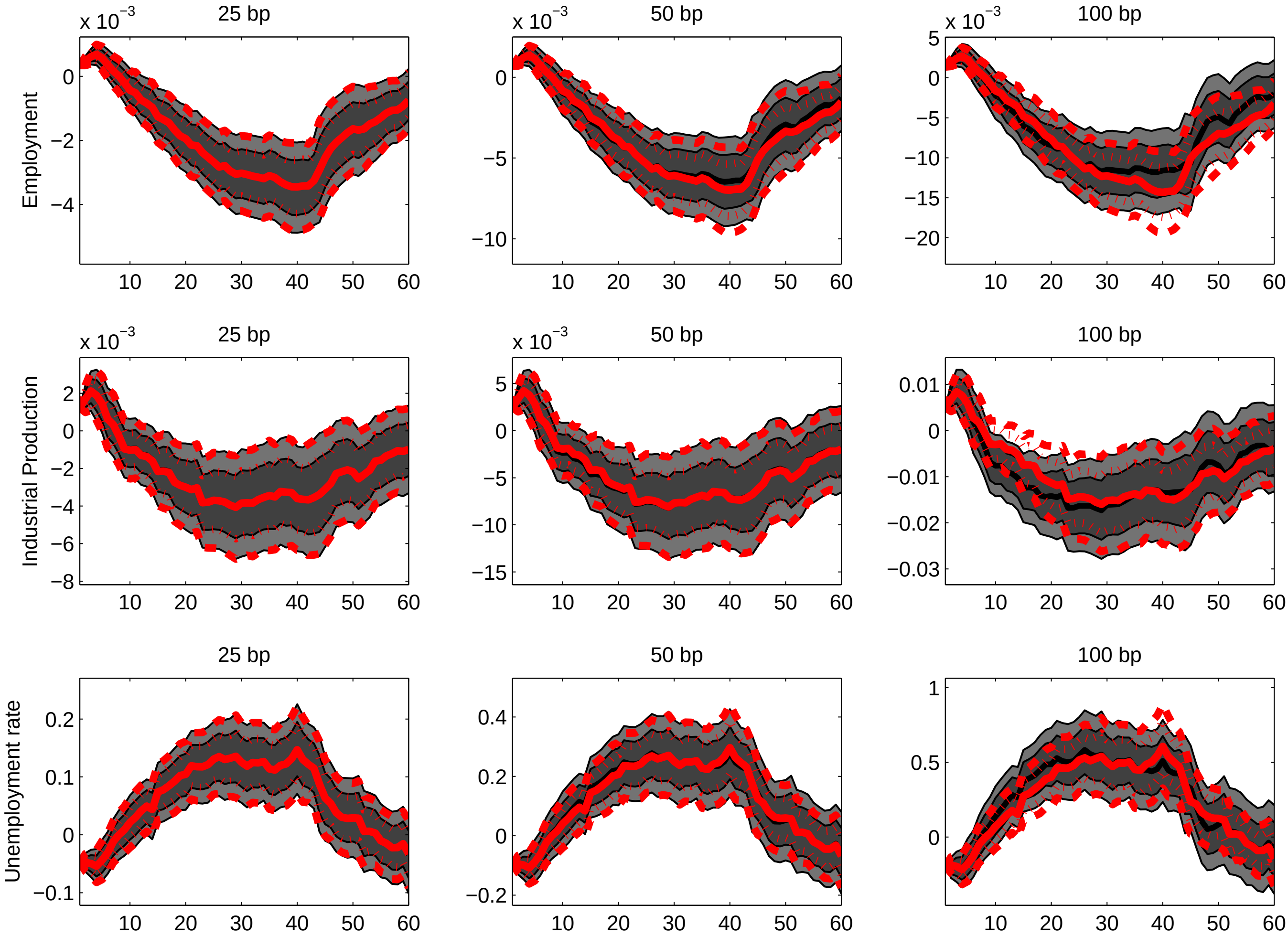
Figures

Figure 1: GZ SPREAD, MOODY'S BAA-AAA SPREAD AND EXCESS BOND PREMIUM



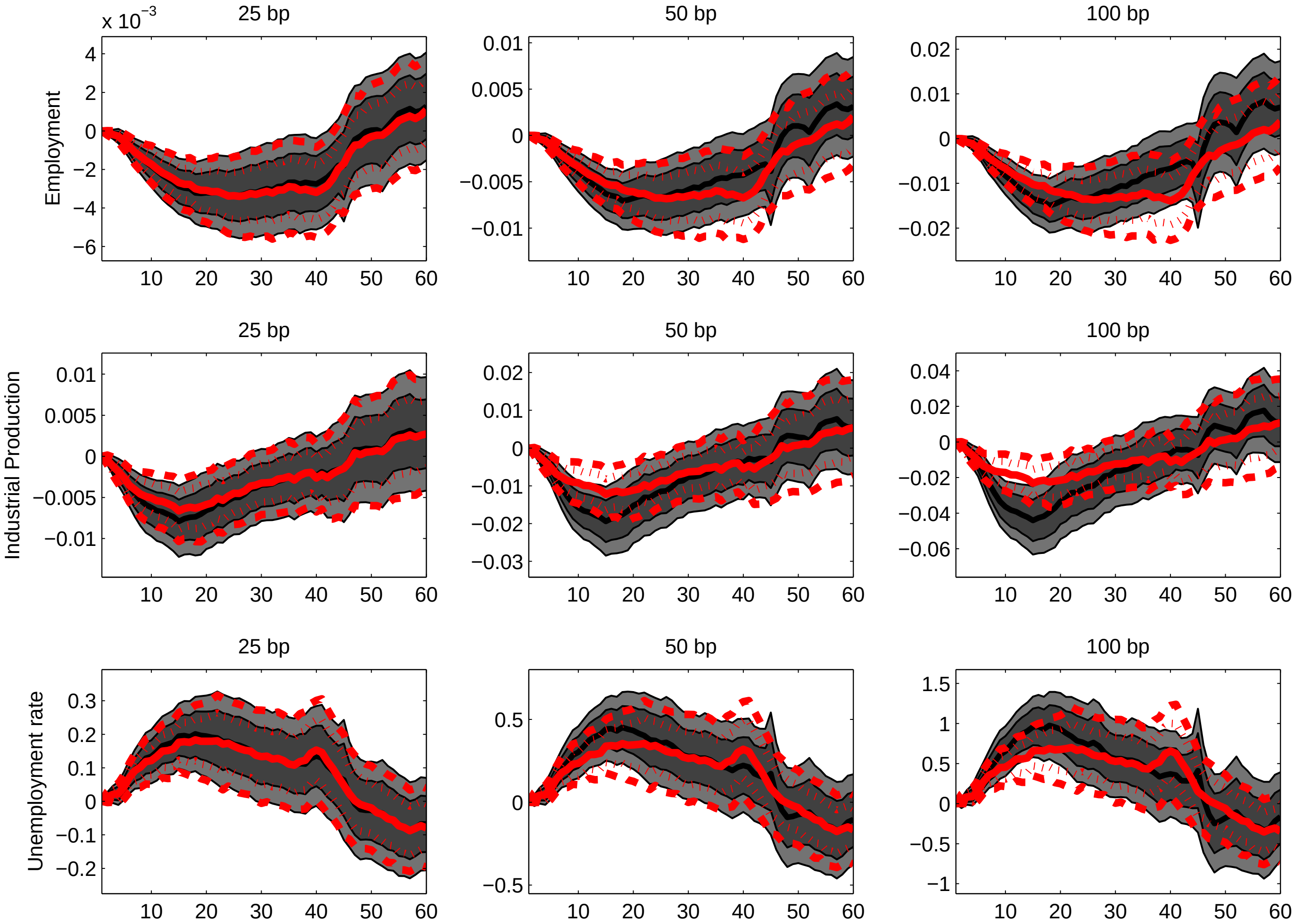
Notes: The figure compares three different indicators of tensions in credit markets, i.e., the GZ spread (red line), the Moody's spread between Seasoned BAA and AAA Corporate Bond Yield (blue line) and the EBP (green line). Sample is 1973:01 - 2012:10.

Figure 2: IRFs to a monetary policy shock, baseline (Specification 1)



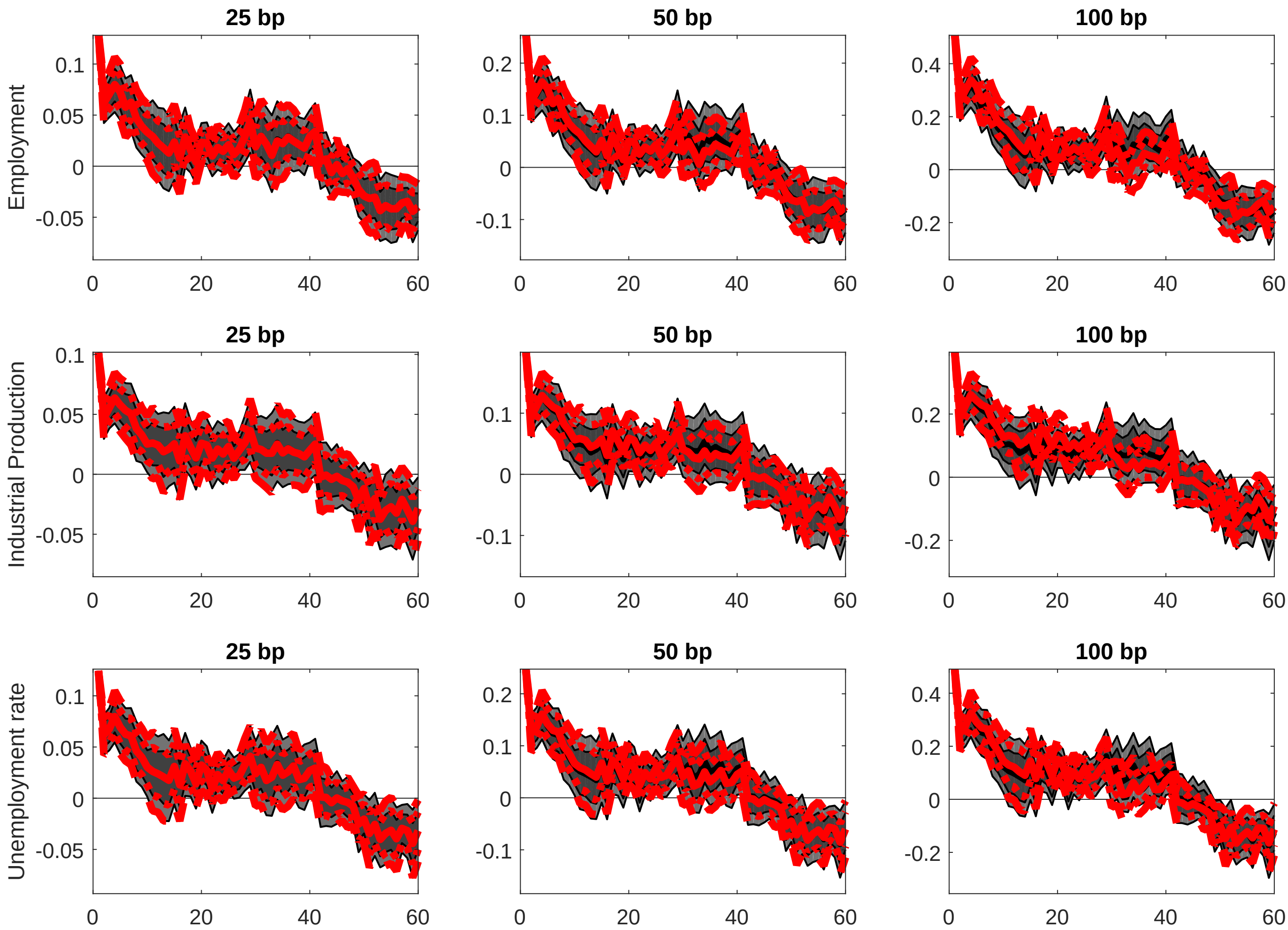
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the policy instrument, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the policy instrument, a monetary easing, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 3: IRFs to a shock to EBP, Cholesky identification, Specification 1



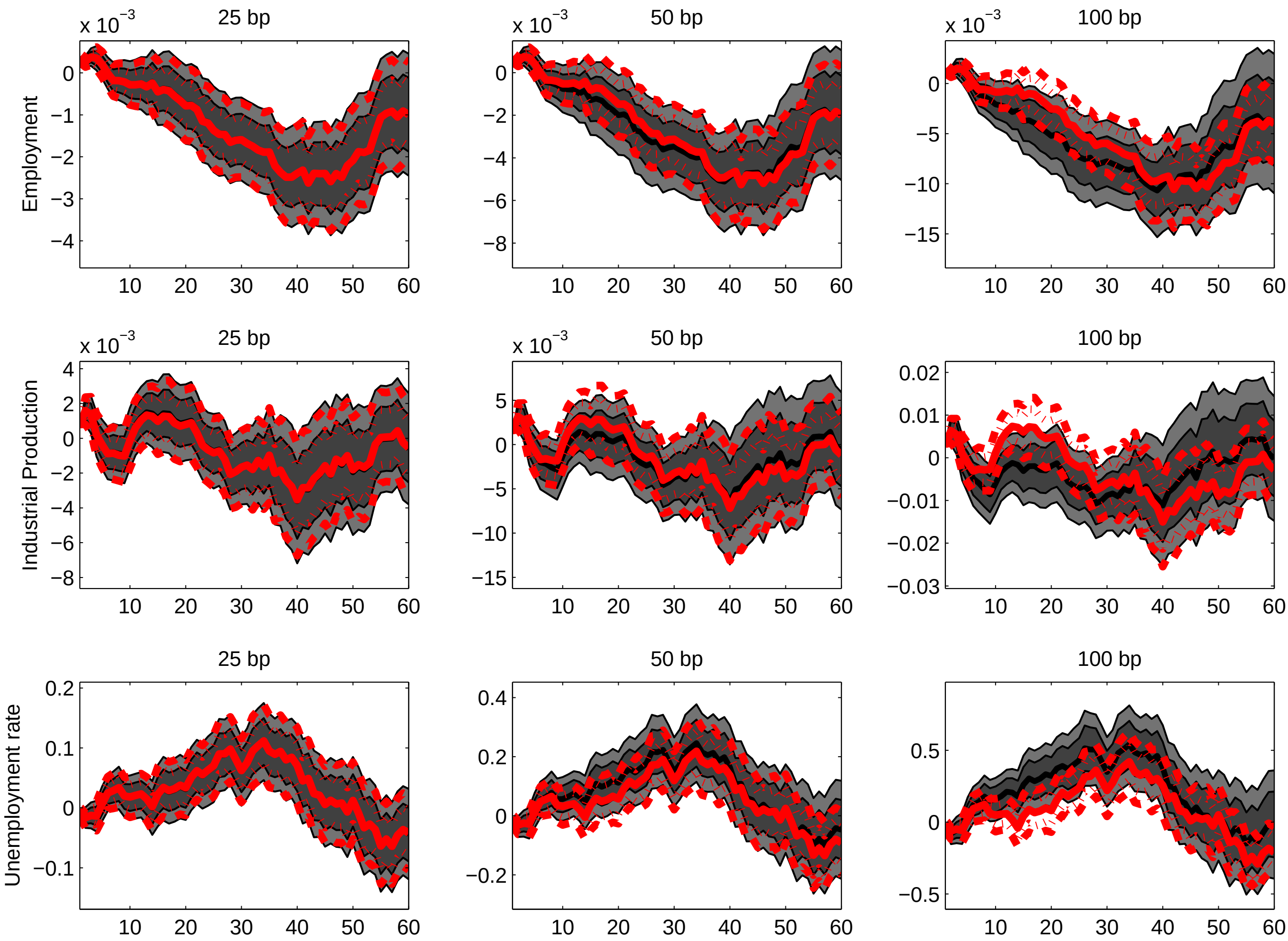
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the policy instrument, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the policy instrument, a monetary easing, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 4: IRFs of EBP to a monetary policy shock, Specification 1



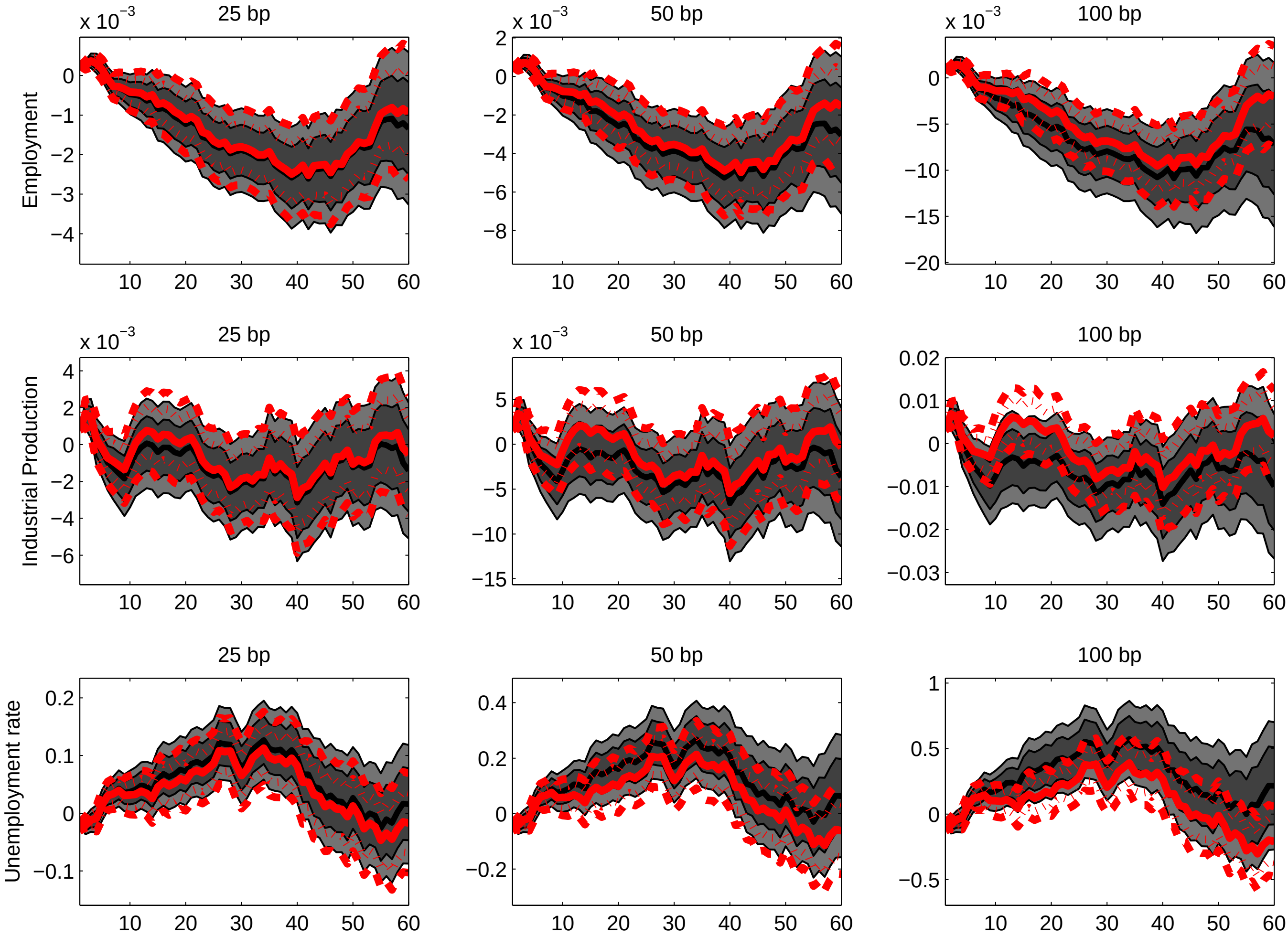
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the policy instrument, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the policy instrument, a monetary easing, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 5: IRFs to a monetary policy shock, Specification 4



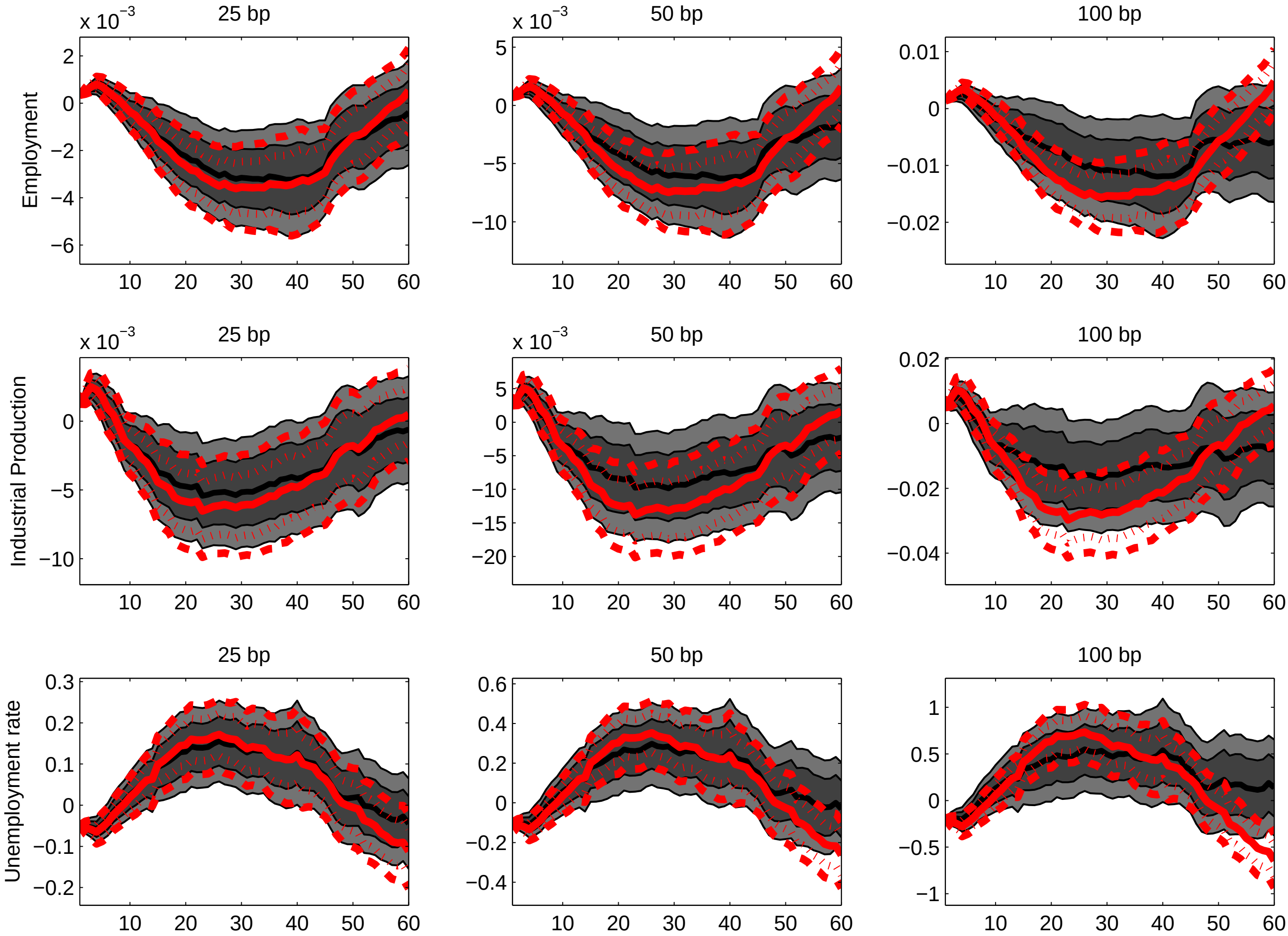
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 6: IRFs to a monetary policy shock, Specification 8



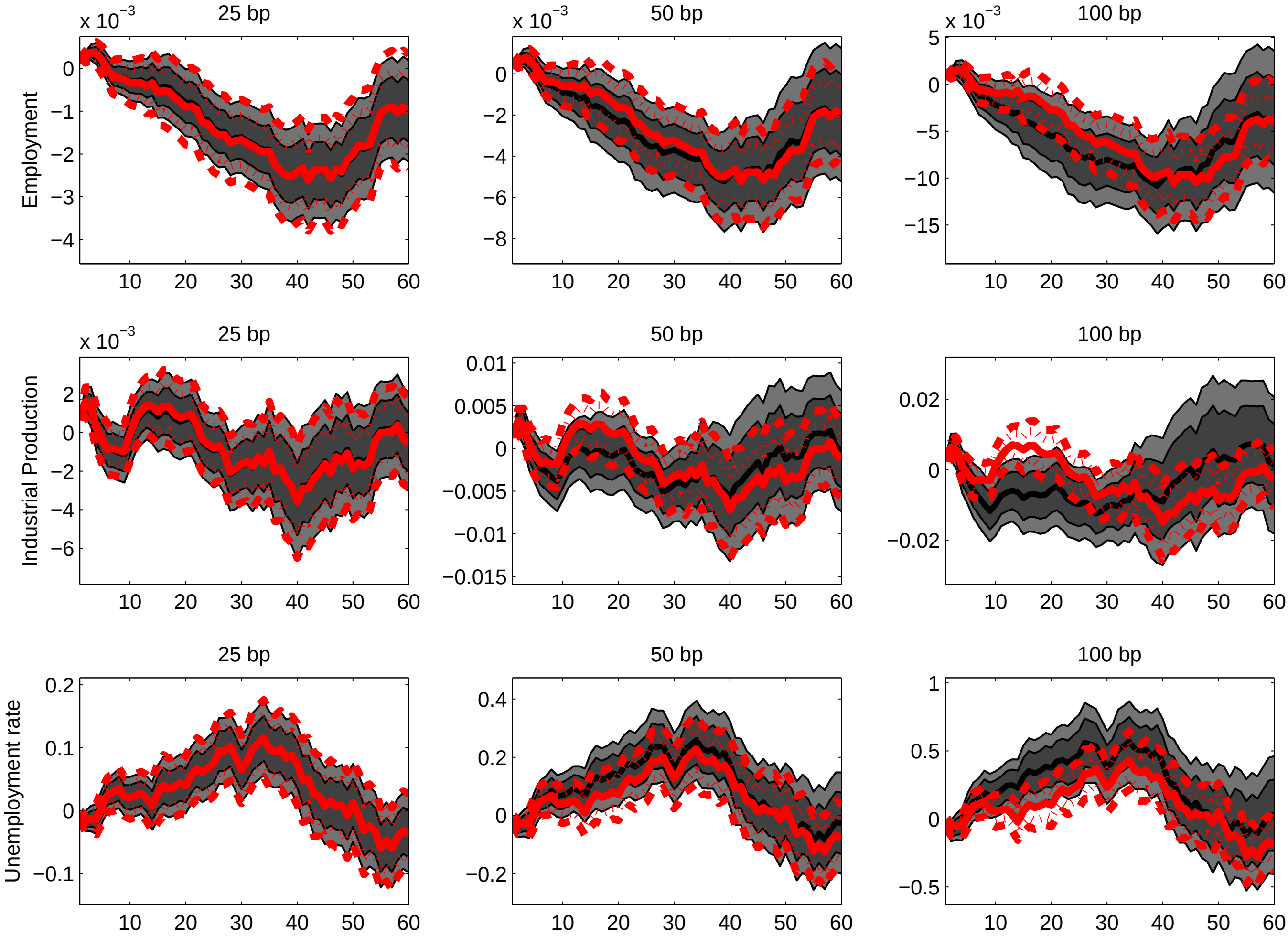
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12months horizon. Sample is 1973:01 - 2012:10.

Figure 7: IRFs to a monetary policy shock, Specification 12



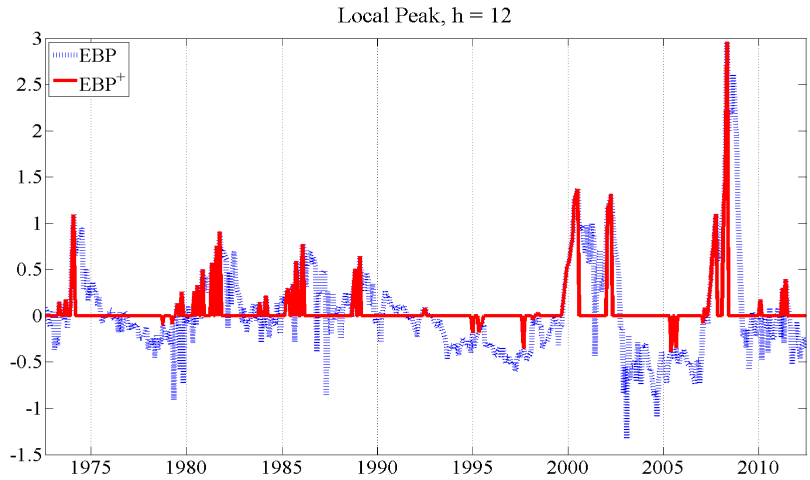
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12months horizon. Sample is 1973:01 - 2012:10.

Figure 8: IRFs to a monetary policy shock, local peaks, conditioning on recessions (Specification 13)

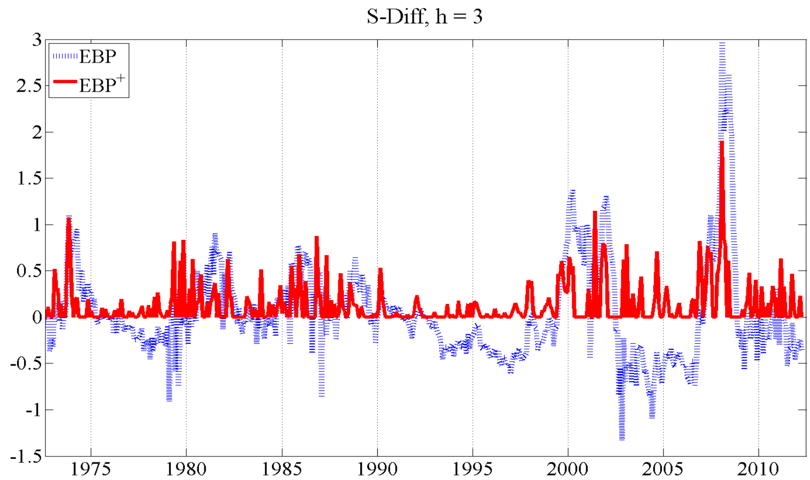


Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

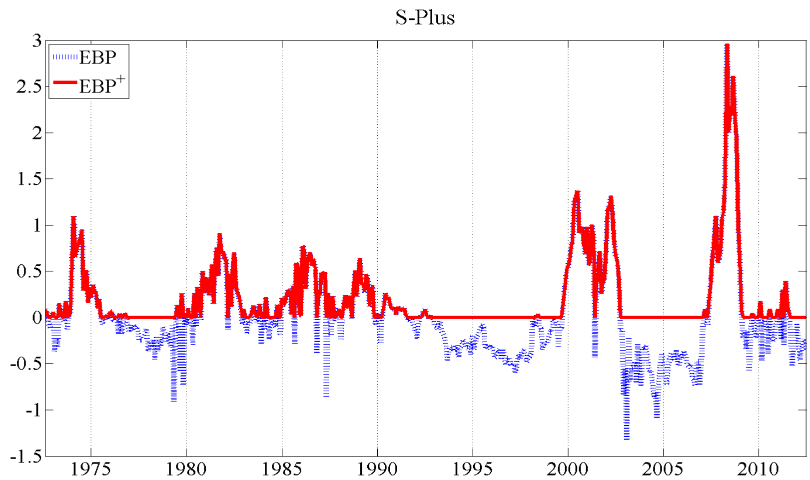
Figure 9: EBP AND ITS TRANSFORMATIONS CAPTURING ASYMMETRIES



(a)



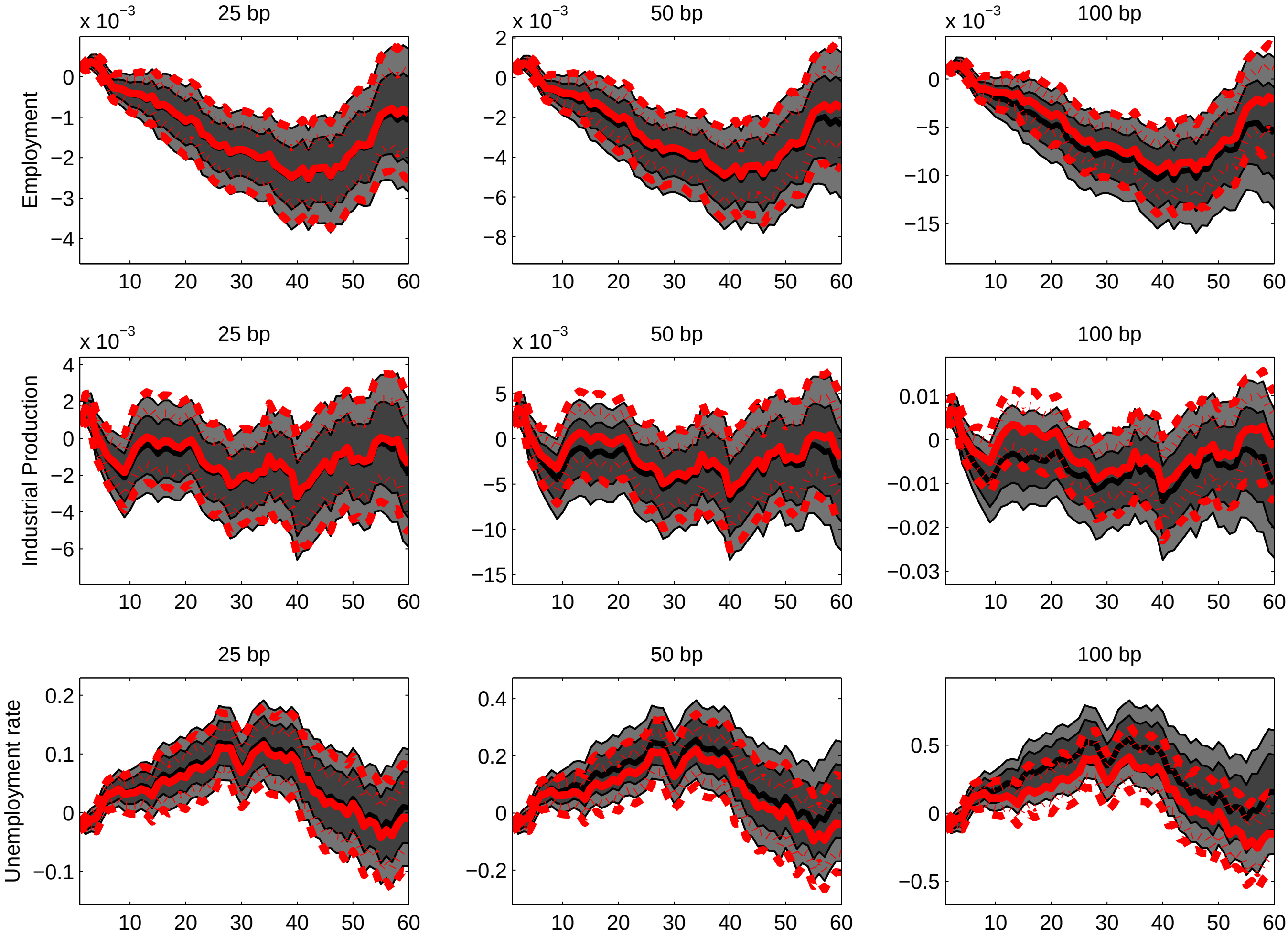
(b)



(c)

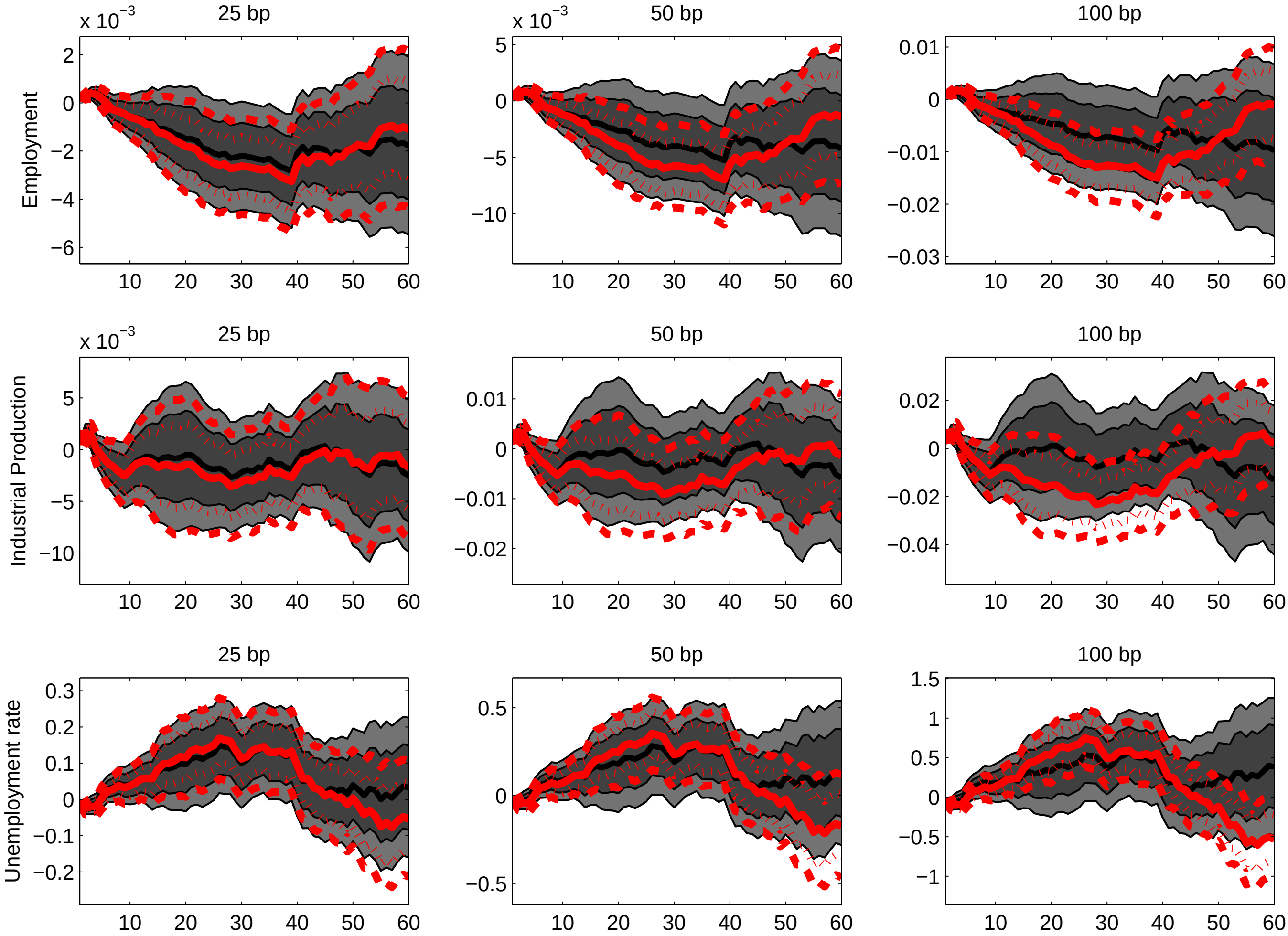
Notes: Each subfigure plots the EBP (x_t) and the related asymmetric indicator built at horizon j ($x_t^+(j)$). The top panel shows the EBP and the local peak transformation, defined as $x_t^+(j) = x_t I[x_t > max(x_{t-1}, x_{t-2}, ..., x_{t-j})]$ with j = 12. The middle panel shows the EBP and the S-diff transformation, defined as $x_t^+(j) = (x_t - x_{t-h}) I[x_t - x_{t-h} > 0]$. The bottom panel shows the EBP and the S-minplus transformation defined as $x_t^+ = x_t I[x_t > 0]$

Figure 10: IRFs to a monetary policy shock, S-diff, conditioning on recessions (Specification 14)



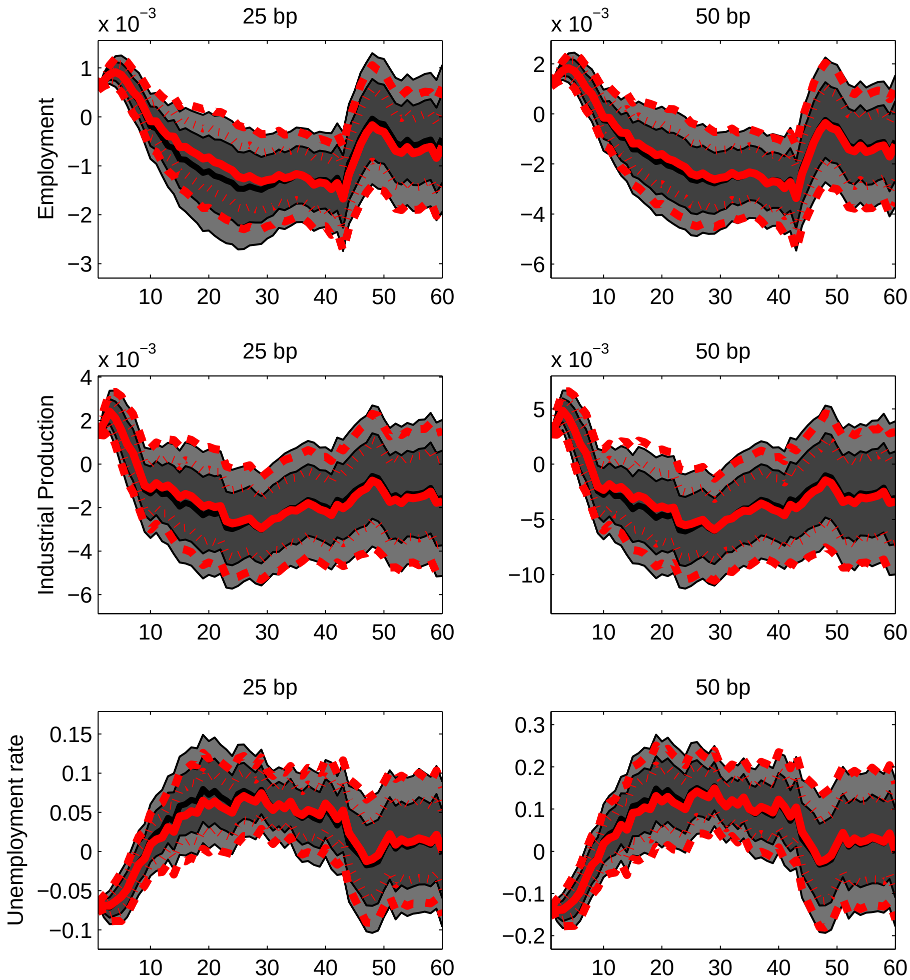
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 11: IRFs to a monetary policy shock, S-plus, conditioning on recessions (Specification 15)



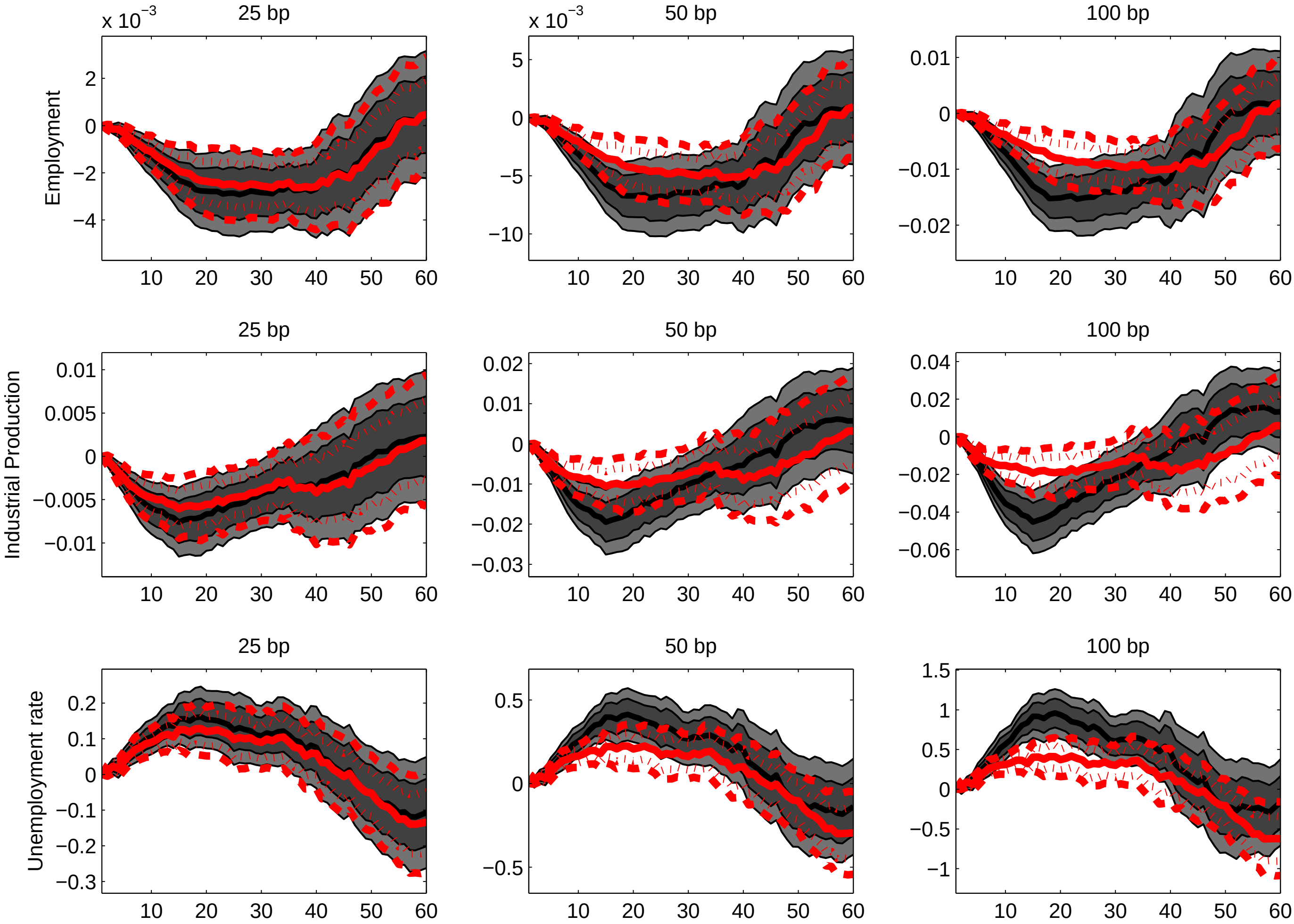
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 12: IRFs to a monetary policy shock, Chicago FCI as measure of asymmetries (Specification 16)



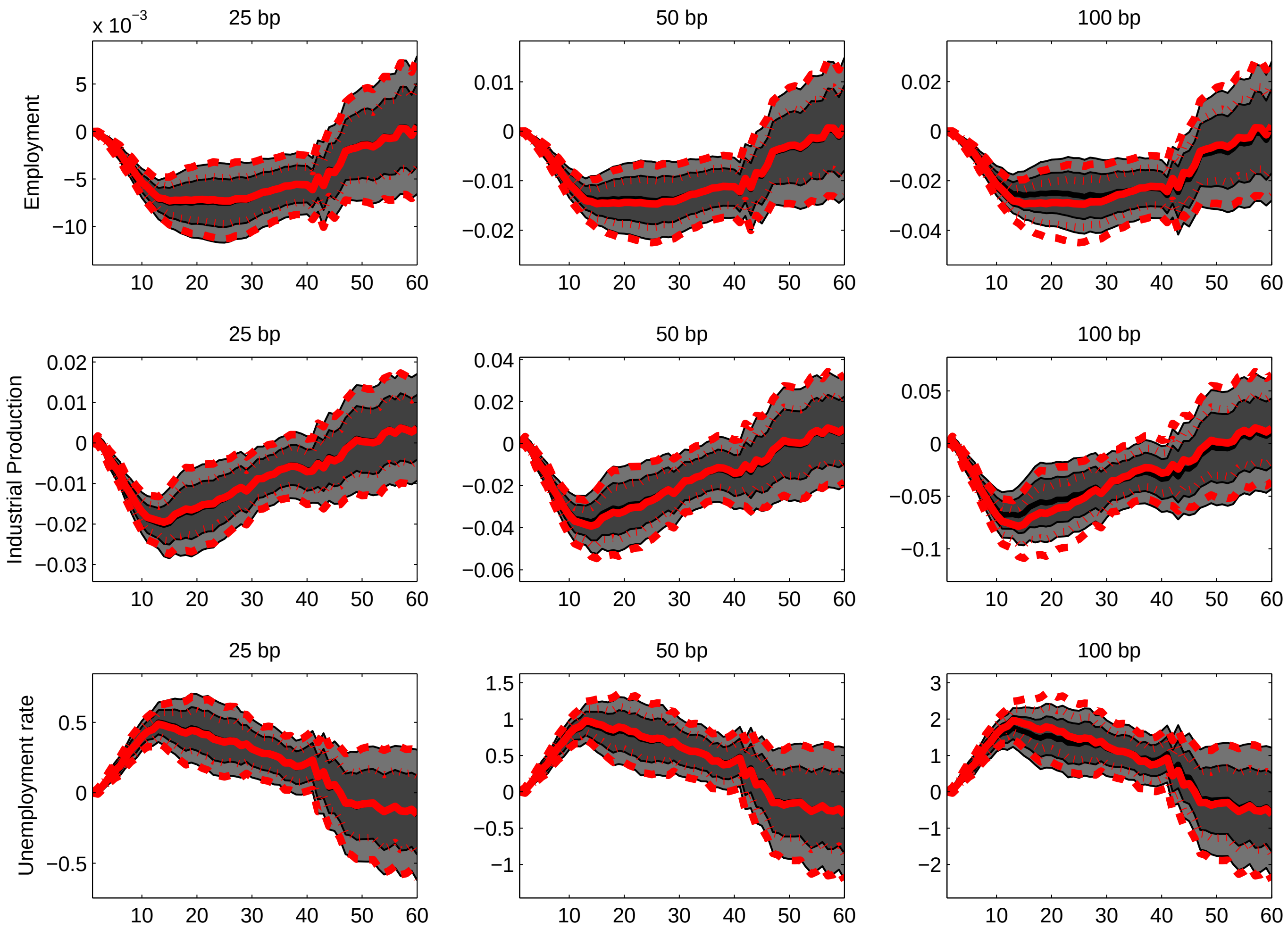
Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 13: IRFs to a monetary policy shock, EBP as measure of asymmetries, measures of volatility and confidence included, Cholesky identification



Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Figure 14: IRFs to a monetary policy shock, Chicago FCI as measure of asymmetries, Cholesky identification



Notes: The black line represents the estimated median impulse response to a positive shock, i.e. an *increase* of the spreads, together with its 68% (the dark grey shaded area) and its 90% (the light grey shaded area). The red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads,together with its 68% (dotted red lines) and its 90% (dashed red lines). From left panel to the right increasing sizes of the shocks are plotted. Here we are conditioning on a given point in time of the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1973:01 - 2012:10.

Appendix

A Monetary policy trade-off in a two-period economy

In Section 2.1 of the paper we examine a stylized two-period economy described by the following equations:

$$\begin{aligned} y_t &= \gamma \Delta s_t + \xi \Delta s_t I_{\Delta s_t > 0} + e_t \\ \Delta s_t &= -(1-\rho) s_{t-1} + i_t \end{aligned}$$

The output gap y_t is affected by a random disturbance e_t and by the variation in credit spreads relative to the previous period, Δs_t. The impact of the spreads on economic activity is negative ($\gamma < 0$) and potentially nonlinear ($\xi \leq 0$). The spread equation comes from a simple AR(1) process $s_t = (1-\rho)s^* + \rho s_{t-1} + i_t$ with $s^* = 0$, where the equilibrium value s^* is set to zero to save notation. We consider an economy that starts off from an equilibrium situation where $y_0 = s_0 = 0$. At time 1 an exogenous shock e_1 takes place, the central bank (CB) observes it and decides whether and how to tackle it by manipulating i_1. No actions and no further shocks take place at time 2. Conditional on the shock e_1, the output gaps at $t = 1$ and 2 are a known function of the policy response:

$$\begin{aligned} y_1 &= \gamma i_1 + \xi i_1 I_{i_1 > 0} + e_1 \\ y_2 &= \gamma \Delta s_2 + \xi \Delta s_2 I_{\Delta s_2 > 0} = -(1-\rho) i_1 \left(\gamma + \xi I_{i_1 < 0}\right) \quad , \end{aligned}$$

where we used the fact that $\Delta s_2 > 0 \Leftrightarrow s_1 < 0 \Leftrightarrow u_1 < 0$, so $I_{\Delta s_2} > 0 = I_{u_1 < 0}$. In other words, given the nature of the spread equation, the nonlinearity is triggered for sure in $t = 2$ if and only if the policy rate is lowered in $t = 1$. We assume that the CB discounts the future gap at a rate $\beta < 1$ and focus on a recession $e_1 < 0$ that gives the CB an incentive to implement monetary stimulus. We consider the optimal policy choice under risk neutrality and risk aversion.

Risk-neutral central bank. For the risk-neutral (RN) CB, the loss function is the expected (or average) output gap over the two periods, which can be written as a function of shock and policy response as follows (the time subscript can be omitted because both are dated time-1):

$$
\begin{aligned}
\ell^{RN}(e,i) &= y_1 + \beta y_2 \\
&= e + \gamma i + \xi I_{i>0} - \beta(1-\rho)(\gamma + \xi I_{i<0})i \\
&= e + \gamma i - \beta(1-\rho)(\gamma+\xi)i
\end{aligned}
$$

(The indicator function can be dropped once we focus on $e < 0$ and thus $i < 0$). The optimal policy choice can be derived by simply setting $\ell^{RN}(e,i) = 0$ and rearranging the terms:

$$
i = -\frac{1}{\gamma}\left[\frac{1}{1-\beta(1-\rho)(1+\xi/\gamma)}\right] e \equiv -\frac{\kappa^{RN}(\xi)}{\gamma} e,
$$

where

$$
\kappa^{RN}(\xi) \equiv \frac{1}{1-\beta(1-\rho)\left(1+\frac{\xi}{\gamma}\right)}
$$

We assume $\beta(1-\rho)(1+\xi/\gamma) < 1$ in order to guarantee $\kappa^{RN}(\xi) > 0$, so that $e < 0$ always implies $i < 0$. [21] Subject to that, one can see that:

$$
\begin{aligned}
i)\ \kappa^{RN}(\xi) &\geq 1 \\
ii)\ \kappa^{RN}(\xi) &= 1 \Leftrightarrow \rho = 1 \text{ or } \beta = 0 \\
iii)\ \kappa^{RN}_{\xi}(\xi) &= -\left[1-\beta(1-\rho)(1+\frac{\xi}{\gamma})\right]^{-2}\frac{-\beta(1-\rho)}{\gamma} = \frac{1}{\gamma}\frac{\beta(1-\rho)}{\left[[1-\beta(1-\rho)]\,(1+\frac{\xi}{\gamma})\right]^2} < 0
\end{aligned}
$$

These are summarised under Result (1) in the paper. With $\beta = 0$ or $\rho = 1$ the CB fully accomodates the shock, in the sense that it simply keeps the time-1 output gap constant at zero (ii). The negative time-2 gap is disregarded ($\beta = 0$) or it does not arise in the first place if the spread is random walk ($\rho = 1$). In general, the response goes beyond full accomodation (i). This multiplier effect arises because, under risk neutrality, the CB chooses a positive gap in $t = 1$ that compensates for the discounted negative gap that will materialize in $t = 2$. The emergence of a non-linearity in the transmission mechanism makes the CB even more aggressive in this respect (iii).

Risk-averse central bank Under risk aversion, the CB minimises the variance of the

[21] The condition is economically sensible – it implies that the policy rate drops (rises) after a negative (positive) shock – and not overly restrictive. It clearly holds instance if $\xi \geqslant \gamma$ and $\rho \leqslant 0.5$, as in this cases it is satisfied as long as $\beta < 1$. A smaller upper bound for β would be consistent with $t = 2$ being a shorthand for some indefinite future period.

output gap around its zero target:

$$\begin{aligned}\ell^{RA}(e,i) &= y_1^2+\beta y_2^2\\ &= (e+\gamma i+\xi I_{i>0})^2+\beta\left[-(1-\rho)(\gamma+\xi I_{i<0})i\right]^2\\ &= e^2+2e\gamma i+\left[\gamma^2+\beta(1-\rho)^2(\gamma+\xi)^2\right]i^2\end{aligned}$$

The first-order condition for this problem is:[22]

$$\begin{aligned}\ell_i^{RA}(e,i) &= 2e\gamma+2[\gamma^2+\beta(1-\rho)^2(\gamma+\xi)^2]i=0\\ i &= -\frac{\gamma}{[\gamma^2+\beta(1-\rho)^2(\gamma+\xi)^2]}e\\ &\equiv -\frac{\kappa^{RA}(\xi)}{\gamma}e,\end{aligned}$$

where

$$\kappa^{RA}(\xi)\equiv\left[\frac{1}{1+\beta(1-\rho)^2\left(1+\frac{\xi}{\gamma}\right)^2}\right]$$

In this case the multiplier has the following properties:

$$\begin{aligned}i)\ \kappa^{RA}(\xi) &\leq 1\\ ii)\ \kappa^{RA}(\xi) &= 1\Leftrightarrow\rho=1\ or\ \beta=0\\ iii)\ \kappa_\xi^{RA}(\xi) &= -\left[1+\beta(1-\rho)^2\left(1+\frac{\xi}{\gamma}\right)^2\right]^{-2}\frac{2}{\gamma}\left(1+\frac{\xi}{\gamma}\right)\\ &= -\frac{1}{\gamma}\frac{2(1+\frac{\xi}{\gamma})}{\left[1+\beta(1-\rho)^2\left(1+\frac{\xi}{\gamma}\right)^2\right]^2}>0,\end{aligned}$$

(where the last inequality in (iii) follows again from $\gamma<0$ and $\xi\leq 0$). Risk aversion generally creates an attenuation effect: relative to the benchmark case of an impatient CB (or a random-walk spread), the interest rate here moves less (i, ii). That implies *a fortiori* that the risk-averse CB acts less then the risk-neutral CB examined above. Furthermore, the nonlinearity works in the opposite direction compared to the risk neutral case, leading to even milder policy interventions (iii).

[22]The second-order condition is satisfied so this identifies the global minimum for the loss function.

B Evidence for euro area and its major countries

In this Appendix we present results of forecasting regressions and structural multivariate models also for the euro area, France, Germany and Italy. However, the credit spreads available for these countries are not directly comparable to the EBP, but, instead to the GZ spread. One has to then keep it in mind when interpreting the results.

B.1 Forecasting regressions

In Tables B-1 – B-4 we present the results for the euro area (EA), France, Germany and Italy. Notice that these tables are organized in four panels. The top two panels show results obtained using the spreads for non-financial corporations (NFC Spread) and relate to, respectively, Industrial Production and the Unemployment rate, while the bottom two refer to the analysis that related the banking credit spreads (Bank Spread) to the same measures of economic activity. Also notice that, since for these economies no distinction between predictable and excess bond premium is available, the baseline predictive regressions are augmented with suitable *local peak* transformations of the overall spreads.

Starting from the EA aggregate (Table B-1), we find that the NFC spread constructed by Gilchrist and Mojon (2014) has useful predictive content for both industrial production and for the unemployment rate at most forecast horizons. As for the Banking spread, on the other hand, the correlation between current financing conditions and future economic activity is rather weak. Turning to the terms capturing asymmetric effects ($NFCSpread^{+}$ and $BankSpread^{+}$) we find that in most cases their impact is significantly different from zero and of the expected sign (i.e. negative in the case of Industrial Production and positive for the Unemployment rate), indicating that they anticipate recessions more reliably than expansions.

A certain degree of cross-country heterogeneity emerges on the euro area. For France and Germany (Tables B-2 and B-3) NFC spreads display significant predictive content for economic activity at short-medium horizons. By contrast, in most cases banking spreads do not correlate significantly with future economic activity. For Italy, instead, the relationship between both NFC and Banking spreads and future economic activity is very strong and robust across forecast horizons (Table B-4).

Turning to non-linear terms, we find that for the French and the German economy, NFC spreads play a significant role in anticipating falls in industrial production, over and above that implied by the linear terms. Yet this result does not carry over to the unemployment rate, which is also affected by the behaviour of other sectors, notably Services. All in all we read this result as suggesting that the impact *on the overall economy* of these spreads is essentially symmetric. As for Banking spreads, the null hypothesis of a symmetric effect can not generally be rejected. In the case of Italy, the non linear terms are almost never associated with coefficients that are significantly different from zero.

Given the results for the single countries, a question arises as to how to reconcile the outcome of the analysis for the euro area as a whole (where evidence of an asymmetric impact of credit spreads is more pervasive) with those for its largest members, where it is rather episodic. Ongoing work, aimed at enlarging the pool of countries under analysis to Spain, points to a clear role for this country in driving the area-wide results.

Summing up, the results of the regression analysis point to the existence of a *dark side* of credit spreads in the sense of Stein (2014) and Kocherlakota (2014), in the U.S.. As for euro-area countries the evidence is more mixed. In particular, for the largest countries the relationship between spreads and economic activity seems to be linear, with the exception of sectorial effects in France and Germany. Nonetheless evidence of asymmetries for the area as a whole does emerge, probably through the impact of other countries that were strongly hit by the Sovereign Debt crisis.

In interpreting the outcome of this analysis we must keep in mind the two limitations that were highlighted in Section 3.2.1. First, the predictive power of risk-premia might derive from an asymmetric response of these prices to current and past bad news on the state of the economy. Second, inference based on regression coefficients in the presence of censored regressors might be misleading. In the next sub-section we therefore turn to multivariate models in which we can trace out the dynamic effect of a structural shock to credit spreads that is orthogonal to the current state of the economy.

B.2 Multivariate models

Results for the euro area, France, Germany and Italy are presented in Figures B-1 to B-10. Panels are organized in a similar manner as for the U.S., bearing in mind that for these economies we only consider two measures of real activity but two different spreads. We keep the comment on these results to a minimum, given that they unequivocally point to the same conclusions.

Starting from the euro area as a whole (Figures B-1 and B-2), a shock to the NFC spread generates a fall in the rate of growth of industrial production and an increase in the unemployment rate. Notice, however, that no clear difference emerges in response to positive, rather than negative shocks, regardless of the size of the shock. The response of these variables to shocks to the Banking spread is imperfectly measured, as the reaction of both the unemployment rate and of industrial production is not significantly different from zero. As hinted in the Introduction this could partly reflect a limitation of this set of indicators (due to the fact that they do not distinguish an ordinary from an excess bond premium). However, it could also suggest that the asymmetric effects estimated in the predictive regressions in the case of the euro area do not reflect a causal link running from the financial to the real sector.

Results for the single countries are essentially in line with those for the euro area as a whole as: (i) NFC spread shocks generally exert a stronger effect than Banking spread shocks (ii) no evidence of non-linear effects emerges.

Wrapping up, when subject to the more stringent test implied by a multivariate structural econometric setup, the evidence of asymmetric response of economic activity to unexpected changes in risk-premia turns out to be confined to the case of large, episodic shocks, of the type observed in the U.S. during the Great Financial Crisis.

Table B-1: Credit spreads, economic activity and non–linearities: Euro Area

Order of local peak		12			24		36		36
Forecast horizon	6	12	18	6	12	18	6	12	18
				Industrial production					
Term Spread	-0.57	-0.63	-0.61	-0.57	-0.63	-0.60	-0.55	-0.63	-0.61
p-val	***0.02***	***0.04***	***0.03***	***0.02***	***0.04***	***0.02***	***0.01***	***0.04***	***0.02***
Real EONIA	0.13	0.21	0.11	0.13	0.21	0.11	0.16	0.23	0.12
p-val	*0.27*	*0.27*	*0.67*	*0.26*	*0.26*	*0.66*	*0.25*	*0.27*	*0.62*
NFC Spread	-0.47	-0.25	-0.23	-0.46	-0.24	-0.22	-0.43	-0.24	-0.24
p-val	***0.00***	*0.17*	*0.44*	***0.00***	*0.16*	*0.41*	***0.00***	*0.16*	*0.36*
NFC Spread$^+$	-0.07	-0.16	-0.14	-0.09	-0.17	-0.17	-0.17	-0.23	-0.17
p-val	*0.28*	***0.00***	***0.03***	*0.20*	***0.00***	***0.06***	***0.09***	***0.00***	***0.09***
$\bar{R}^2$	0.44	0.42	0.38	0.44	0.42	0.38	0.45	0.43	0.38
				Unemployment rate					
Term Spread	0.18	0.25	0.28	0.17	0.24	0.27	0.17	0.24	0.27
p-val	*0.22*	*0.25*	*0.20*	*0.22*	*0.25*	*0.20*	*0.21*	*0.24*	*0.19*
Real EONIA	-0.10	-0.15	-0.15	-0.10	-0.14	-0.15	-0.12	-0.16	-0.16
p-val	*0.39*	*0.51*	*0.71*	*0.39*	*0.49*	*0.69*	*0.42*	*0.56*	*0.76*
NFC Spread	0.37	0.38	0.42	0.36	0.37	0.41	0.36	0.38	0.42
p-val	***0.02***	*0.12*	***0.08***	***0.02***	*0.14*	***0.10***	***0.01***	*0.13*	***0.08***
NFC Spread$^+$	0.07	0.10	0.10	0.10	0.13	0.13	0.13	0.15	0.13
p-val	*0.18*	*0.17*	*0.13*	***0.10***	***0.10***	*0.11*	***0.09***	***0.04***	***0.09***
$\bar{R}^2$	0.70	0.54	0.41	0.70	0.54	0.42	0.70	0.54	0.41
				Industrial production					
Term Spread	-0.54	-0.64	-0.57	-0.53	-0.64	-0.57	-0.53	-0.64	-0.57
p-val	***0.03***	***0.00***	***0.00***	***0.03***	***0.00***	***0.00***	***0.03***	***0.00***	***0.00***
Real EONIA	0.15	0.16	-0.15	0.17	0.17	-0.14	0.18	0.17	-0.15
p-val	*0.49*	*0.47*	*0.61*	*0.45*	*0.45*	*0.50*	*0.44*	*0.46*	*0.54*
Bank Spread	-0.17	-0.16	-0.38	-0.15	-0.15	-0.36	-0.15	-0.15	-0.38
p-val	*0.40*	*0.44*	*0.14*	*0.46*	*0.47*	***0.05***	*0.49*	*0.51*	***0.06***
Bank Spread$^+$	-0.25	-0.24	-0.16	-0.31	-0.27	-0.20	-0.33	-0.27	-0.16
p-val	0.13	***0.03***	***0.00***	0.12	***0.01***	***0.00***	0.13	***0.02***	***0.00***
$\bar{R}^2$	0.36	0.38	0.40	0.37	0.39	0.40	0.37	0.39	0.40
				Unemployment rate					
Term Spread	0.20	0.28	0.28	0.18	0.26	0.27	0.19	0.27	0.28
p-val	*0.24*	***0.05***	***0.07***	*0.25*	***0.06***	***0.07***	*0.26*	***0.08***	***0.08***
Real EONIA	-0.09	-0.08	0.00	-0.11	-0.09	0.00	-0.11	-0.09	0.01
p-val	*0.67*	*0.88*	*0.99*	*0.61*	*0.82*	*1.00*	*0.62*	*0.83*	*0.97*
Bank Spread	0.08	0.14	0.29	0.06	0.12	0.28	0.07	0.14	0.31
p-val	*0.64*	*0.69*	*0.23*	*0.73*	*0.69*	*0.23*	*0.70*	*0.64*	*0.22*
Bank Spread$^+$	0.21	0.19	0.20	0.27	0.25	0.21	0.25	0.22	0.17
p-val	***0.10***	***0.06***	***0.00***	***0.04***	***0.00***	***0.00***	***0.11***	***0.01***	***0.00***
$\bar{R}^2$	0.65	0.49	0.37	0.66	0.50	0.37	0.66	0.49	0.36

Notes: Sample is 1999:01 - 2014:10. Dependent variables is $\nabla^h Y_{t+h}$, where Y_t denotes the respective economic activity variable in the subpanel title in month t and h is the forecasting horizon. *Order of local peak* represents the number of periods over which the asymmetric term of the financial variable is computed. Each regressions also include a constant and p lags of the dependent variable (not reported), where p is chosen by the BIC. Entries in the table denote the standardized estimates of the OLS coefficients associated with each financial indicator, whereas italics terms are the p-values computed by means of the Newey–West (1987) correction.

Table B-2: Credit spreads, economic activity and non–linearities: France

Order of local peak		12			24		36		36
Forecast horizon	6	12	18	6	12	18	6	12	18
				Industrial production					
Term Spread	0.71	0.74	0.76	0.62	0.73	0.75	0.62	0.73	0.75
p-val	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Real EONIA	4.04	3.53	2.14	4.03	3.53	2.15	4.18	3.65	2.18
p-val	***0.00***	***0.00***	***0.03***	***0.00***	***0.00***	***0.04***	***0.00***	***0.00***	***0.03***
NFC Spread	-0.40	-0.19	-0.15	-0.35	-0.18	-0.14	-0.33	-0.16	-0.13
p-val	***0.00***	*0.15*	*0.52*	***0.00***	*0.16*	*0.53*	***0.00***	*0.20*	*0.54*
NFC Spread$^+$	-0.15	-0.13	-0.03	-0.14	-0.14	-0.05	-0.17	-0.17	-0.06
p-val	***0.01***	***0.01***	*0.71*	***0.01***	***0.01***	*0.54*	***0.01***	***0.00***	*0.46*
$\bar{R}^2$	0.48	0.49	0.44	0.48	0.49	0.44	0.48	0.50	0.45
				Unemployment rate					
Term Spread	-0.29	-0.37	-0.33	-0.29	-0.37	-0.32	-0.29	-0.36	-0.32
p-val	*0.13*	***0.00***	***0.00***	***0.09***	***0.00***	***0.00***	***0.02***	***0.00***	***0.00***
Real EONIA	-0.75	-0.84	-0.75	-0.75	-0.84	-0.75	-0.75	-0.84	-0.75
p-val	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
NFC Spread	0.37	0.50	0.50	0.36	0.49	0.49	0.36	0.48	0.48
p-val	***0.01***	***0.00***	***0.00***	***0.01***	***0.00***	***0.00***	***0.01***	***0.00***	***0.00***
NFC Spread$^+$	0.01	-0.04	-0.05	0.03	-0.02	-0.03	0.04	0.00	-0.02
p-val	*0.68*	*0.42*	*0.35*	*0.38*	*0.66*	*0.50*	*0.12*	*0.95*	*0.58*
$\bar{R}^2$	0.73	0.63	0.53	0.73	0.63	0.53	0.73	0.63	0.53
				Industrial production					
Term Spread	0.71	0.85	0.86	0.68	0.82	0.83	0.66	0.81	0.83
p-val	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.01***	***0.00***
Real EONIA	2.59	2.54	1.39	2.62	2.58	1.42	2.71	2.63	1.44
p-val	***0.03***	***0.03***	*0.37*	***0.02***	***0.03***	*0.36*	***0.02***	***0.03***	*0.35*
Bank Spread	-0.37	-0.30	-0.34	-0.32	-0.26	-0.30	-0.31	-0.24	-0.29
p-val	***0.02***	***0.08***	*0.23*	***0.03***	*0.13*	*0.26*	***0.04***	*0.16*	*0.27*
Bank Spread$^+$	-0.21	-0.12	-0.04	-0.30	-0.19	-0.10	-0.36	-0.25	-0.12
p-val	*0.19*	*0.25*	*0.75*	*0.18*	*0.16*	*0.49*	***0.10***	***0.05***	*0.37*
$\bar{R}^2$	0.42	0.47	0.46	0.43	0.48	0.46	0.44	0.49	0.47
				Unemployment rate					
Term Spread	-0.30	-0.38	-0.35	-0.30	-0.39	-0.35	-0.30	-0.37	-0.34
p-val	***0.06***	***0.03***	***0.05***	***0.06***	***0.03***	***0.04***	***0.05***	***0.03***	***0.05***
Real EONIA	-0.59	-0.66	-0.61	-0.59	-0.66	-0.60	-0.59	-0.67	-0.61
p-val	***0.00***	***0.00***	***0.02***	***0.00***	***0.00***	***0.01***	***0.00***	***0.00***	***0.01***
Bank Spread	0.21	0.30	0.31	0.22	0.31	0.31	0.22	0.30	0.30
p-val	*0.15*	*0.22*	*0.27*	*0.14*	*0.16*	*0.25*	*0.12*	*0.16*	*0.25*
Bank Spread$^+$	0.13	0.13	0.08	0.12	0.11	0.08	0.14	0.15	0.11
p-val	*0.18*	*0.38*	*0.53*	*0.27*	*0.45*	*0.53*	*0.25*	*0.25*	*0.39*
$\bar{R}^2$	0.67	0.54	0.43	0.67	0.53	0.43	0.67	0.54	0.43

Notes: Sample is 1999:01 - 2014:10. Dependent variables is $\nabla^h Y_{t+h}$, where Y_t denotes the respective economic activity variable in the subpanel title in month t and h is the forecasting horizon. *Order of local peak* represents the number of periods over which the asymmetric term of the financial variable is computed. Each regressions also include a constant and p lags of the dependent variable (not reported), where p is chosen by the BIC. Entries in the table denote the standardized estimates of the OLS coefficients associated with each financial indicator, whereas italics terms are the p-values computed by means of the Newey–West (1987) correction.

Table B-3: Credit spreads, economic activity and non–linearities: Germany

Order of local peak		12			24		36		36
Forecast horizon	6	12	18	6	12	18	6	12	18
				Industrial production					
Term Spread	0.65	0.66	0.65	0.57	0.66	0.64	0.55	0.64	0.63
p-val	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Real EONIA	1.88	1.80	0.56	1.90	1.84	0.61	2.17	2.09	0.79
p-val	**0.07**	**0.04**	0.37	**0.07**	**0.03**	0.31	**0.02**	**0.02**	0.22
NFC Spread	-0.44	-0.23	-0.13	-0.38	-0.22	-0.11	-0.37	-0.21	-0.11
p-val	**0.00**	0.11	0.26	**0.00**	0.11	0.35	**0.00**	0.13	0.41
NFC Spread$^+$	-0.04	-0.10	-0.12	-0.04	-0.12	-0.15	-0.12	-0.19	-0.19
p-val	0.40	**0.02**	**0.00**	0.33	**0.03**	**0.00**	**0.02**	**0.02**	**0.03**
$\bar{R}^2$	0.46	0.52	0.51	0.46	0.52	0.51	0.47	0.53	0.52
				Unemployment rate					
Term Spread	-0.11	-0.19	-0.18	-0.10	-0.18	-0.18	-0.09	-0.18	-0.18
p-val	0.52	0.34	**0.58**	0.55	0.38	**0.58**	0.58	0.40	**0.59**
Real EONIA	0.11	0.15	0.23	0.11	0.15	0.23	0.09	0.14	0.22
p-val	0.38	0.51	0.57	0.40	0.53	0.56	0.49	0.58	0.59
NFC Spread	0.22	0.25	0.16	0.22	0.24	0.16	0.20	0.24	0.16
p-val	**0.00**	**0.04**	0.59	**0.00**	**0.03**	0.60	**0.00**	**0.03**	0.59
NFC Spread$^+$	-0.02	0.01	0.05	0.00	0.04	0.06	0.05	0.05	0.07
p-val	0.75	0.68	0.27	0.95	0.44	0.22	0.40	0.32	0.25
$\bar{R}^2$	0.59	0.40	0.35	0.59	0.40	0.35	0.60	0.40	0.35
				Industrial production					
Term Spread	0.58	0.74	0.73	0.58	0.74	0.74	0.57	0.74	0.68
p-val	**0.00**	**0.02**	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**	**0.02**	**0.01**
Real EONIA	0.96	0.83	-0.14	0.94	0.78	-0.36	1.12	0.85	-1.18
p-val	0.56	0.72	0.96	0.58	0.76	0.89	0.54	0.73	0.70
Bank Spread	-0.19	-0.19	-0.17	-0.20	-0.20	-0.22	-0.19	-0.20	-0.31
p-val	0.25	0.44	0.63	0.25	0.44	0.54	0.30	0.44	0.43
Bank Spread$^+$	-0.30	-0.16	-0.14	-0.30	-0.13	-0.10	-0.33	-0.15	-0.07
p-val	0.12	**0.10**	**0.03**	0.18	0.23	0.13	0.15	0.16	0.43
$\bar{R}^2$	0.41	0.49	0.49	0.40	0.48	0.49	0.41	0.49	0.50
				Unemployment rate					
Term Spread	-0.08	-0.18	-0.19	-0.08	-0.18	-0.20	-0.08	-0.18	-0.20
p-val	0.63	0.49	0.47	0.62	0.50	0.47	0.62	0.50	0.45
Real EONIA	0.16	0.23	0.29	0.17	0.23	0.30	0.17	0.23	0.31
p-val	0.46	0.55	0.50	0.45	0.55	0.52	0.48	0.56	0.51
Bank Spread	0.10	0.15	0.12	0.11	0.16	0.13	0.11	0.16	0.14
p-val	0.50	0.59	0.72	0.46	0.58	0.73	0.48	0.58	0.71
Bank Spread$^+$	0.16	0.11	0.02	0.13	0.09	0.00	0.14	0.10	-0.01
p-val	0.32	0.32	0.82	0.47	0.39	0.99	0.47	0.41	0.89
$\bar{R}^2$	0.59	0.37	0.34	0.58	0.37	0.34	0.58	0.37	0.34

Notes: Sample is 1999:01 - 2014:10. Dependent variables is $\nabla^h Y_{t+h}$, where Y_t denotes the respective economic activity variable in the subpanel title in month t and h is the forecasting horizon. *Order of local peak* represents the number of periods over which the asymmetric term of the financial variable is computed. Each regressions also include a constant and p lags of the dependent variable (not reported), where p is chosen by the BIC. Entries in the table denote the standardized estimates of the OLS coefficients associated with each financial indicator, whereas italics terms are the p-values computed by means of the Newey–West (1987) correction.

Table B-4: CREDIT SPREADS, ECONOMIC ACTIVITY AND NON–LINEARITIES: ITALY

Order of local peak		12			24		36		36
Forecast horizon	6	12	18	6	12	18	6	12	18
				Industrial production					
Term Spread	1.23	1.10	0.89	1.08	1.09	0.88	1.09	1.10	0.91
p-val	**0.01**	**0.04**	**0.09**	**0.00**	**0.03**	**0.09**	**0.01**	**0.03**	**0.08**
Real EONIA	7.14	6.38	3.08	7.18	6.41	3.10	7.14	6.37	3.05
p-val	**0.07**	0.17	0.37	**0.06**	0.17	0.37	**0.08**	0.17	0.38
NFC Spread	-0.91	-0.64	-0.59	-0.79	-0.63	-0.58	-0.81	-0.66	-0.64
p-val	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**	**0.02**
NFC Spread$^+$	0.00	-0.01	-0.03	-0.03	-0.04	-0.05	0.00	0.00	0.02
p-val	0.96	0.78	0.42	0.66	0.42	0.25	0.99	0.95	0.70
$\bar{R}^2$	0.46	0.37	0.23	0.46	0.37	0.23	0.46	0.37	0.23
				Unemployment rate					
Term Spread	0.05	-0.08	-0.69	0.07	-0.07	-0.67	0.04	-0.10	-0.71
p-val	0.81	0.83	**0.00**	0.74	0.85	**0.00**	0.83	0.79	**0.01**
Real EONIA	-0.34	-0.63	-0.81	-0.35	-0.63	-0.81	-0.34	-0.63	-0.81
p-val	0.48	0.24	0.11	0.47	0.23	0.11	0.44	0.25	0.13
NFC Spread	0.56	0.66	0.82	0.53	0.64	0.80	0.58	0.69	0.85
p-val	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**	**0.04**
NFC Spread$^+$	0.03	-0.03	-0.09	0.07	0.00	-0.06	0.01	-0.07	-0.12
p-val	0.77	0.58	0.15	0.38	0.97	0.33	0.89	0.29	0.15
$\bar{R}^2$	0.58	0.52	0.53	0.58	0.52	0.53	0.57	0.52	0.54
				Industrial production					
Term Spread	1.40	1.52	1.31	1.38	1.50	1.30	1.39	1.52	1.32
p-val	**0.00**	**0.01**	**0.01**	**0.00**	**0.01**	**0.01**	**0.00**	**0.01**	**0.01**
Real EONIA	6.51	5.60	2.43	6.61	5.65	2.46	6.56	5.60	2.39
p-val	**0.07**	0.14	0.45	**0.06**	0.13	0.43	**0.06**	0.14	0.43
Bank Spread	-1.05	-1.09	-1.12	-1.01	-1.06	-1.10	-1.03	-1.09	-1.15
p-val	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Bank Spread$^+$	-0.03	-0.01	0.01	-0.10	-0.06	-0.03	-0.06	-0.01	0.05
p-val	0.80	0.92	0.91	0.52	0.60	0.74	0.77	0.97	0.49
$\bar{R}^2$	0.43	0.44	0.36	0.44	0.44	0.36	0.43	0.44	0.36
				Unemployment rate					
Term Spread	-0.07	-0.28	-0.41	-0.03	-0.27	-0.41	-0.05	-0.29	-0.44
p-val	0.75	0.37	0.26	0.89	0.44	0.28	0.81	0.34	0.26
Real EONIA	-0.28	-0.55	-0.68	-0.28	-0.53	-0.68	-0.29	-0.55	-0.67
p-val	0.54	0.39	0.24	0.50	0.41	0.22	0.47	0.39	0.24
Bank Spread	0.72	1.00	0.92	0.62	0.96	0.92	0.68	1.01	0.99
p-val	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	**0.01**
Bank Spread$^+$	0.07	-0.08	0.02	0.21	0.00	0.02	0.12	-0.10	-0.07
p-val	0.52	0.48	0.74	**0.05**	0.99	0.84	0.37	0.56	0.44
$\bar{R}^2$	0.58	0.58	0.57	0.59	0.57	0.57	0.59	0.58	0.57

Notes: Sample is 1999:01 - 2014:10. Dependent variables is $\nabla^h Y_{t+h}$, where Y_t denotes the respective economic activity variable in the subpanel title in month t and h is the forecasting horizon. *Order of local peak* represents the number of periods over which the asymmetric term of the financial variable is computed. Each regressions also include a constant and p lags of the dependent variable (not reported), where p is chosen by the BIC. Entries in the table denote the standardized estimates of the OLS coefficients associated with each financial indicator, whereas italics terms are the p-values computed by means of the Newey–West (1987) correction.

Figure B-1: Euro area and main countries: corporate credit spreads

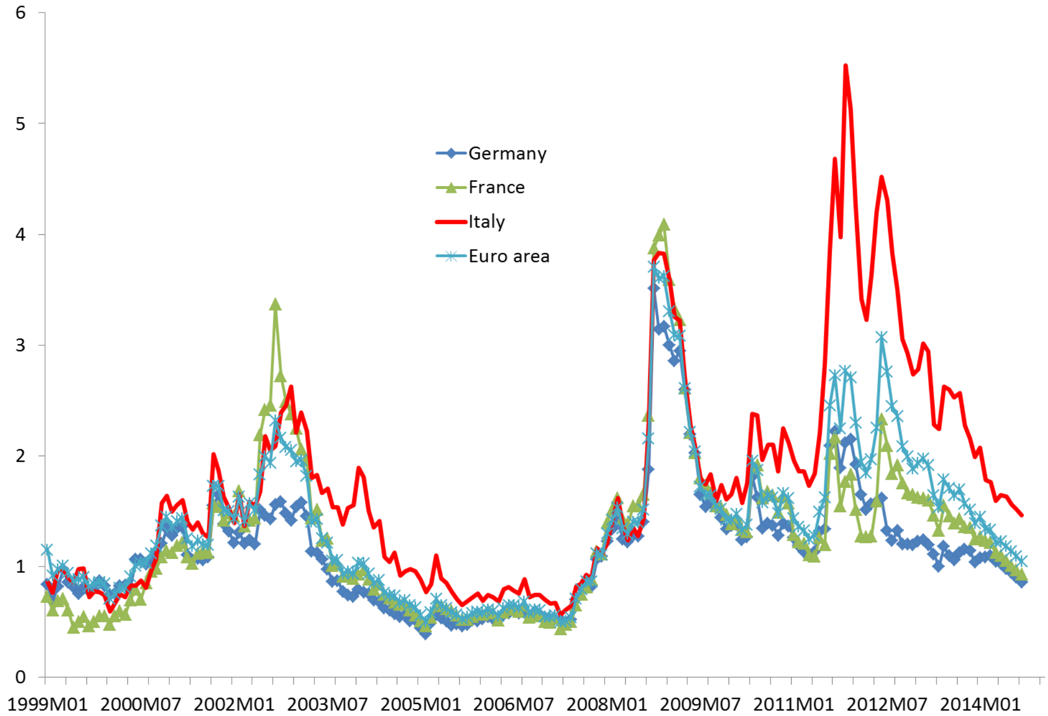


Figure B-2: Euro area and main countries: banking credit spreads

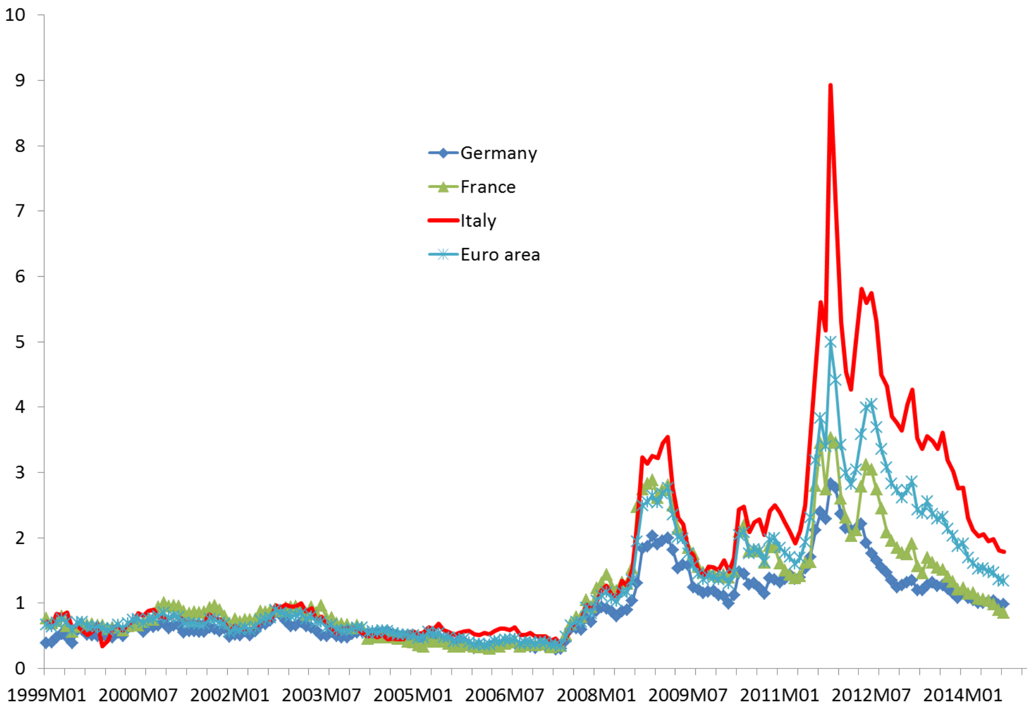
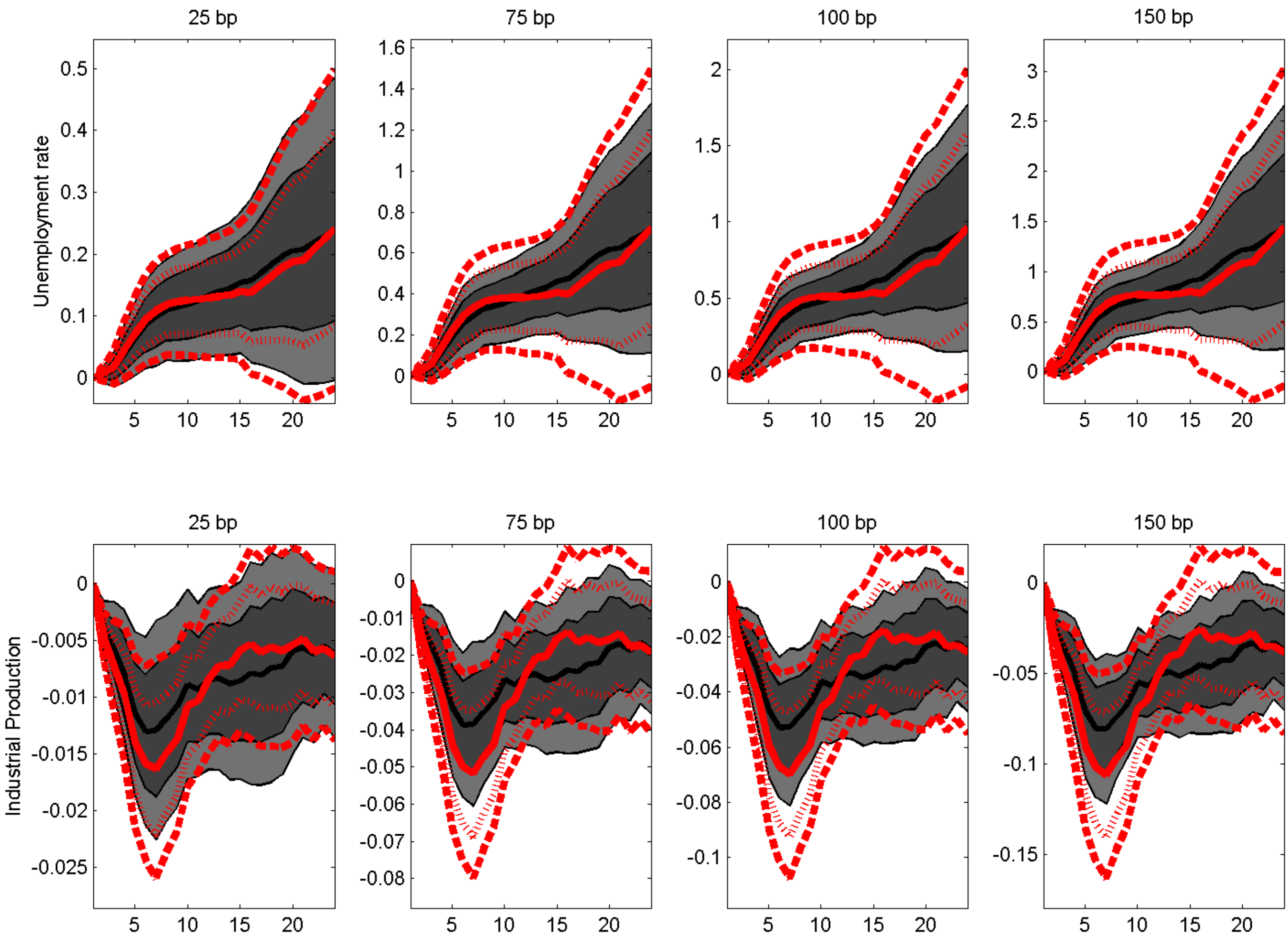
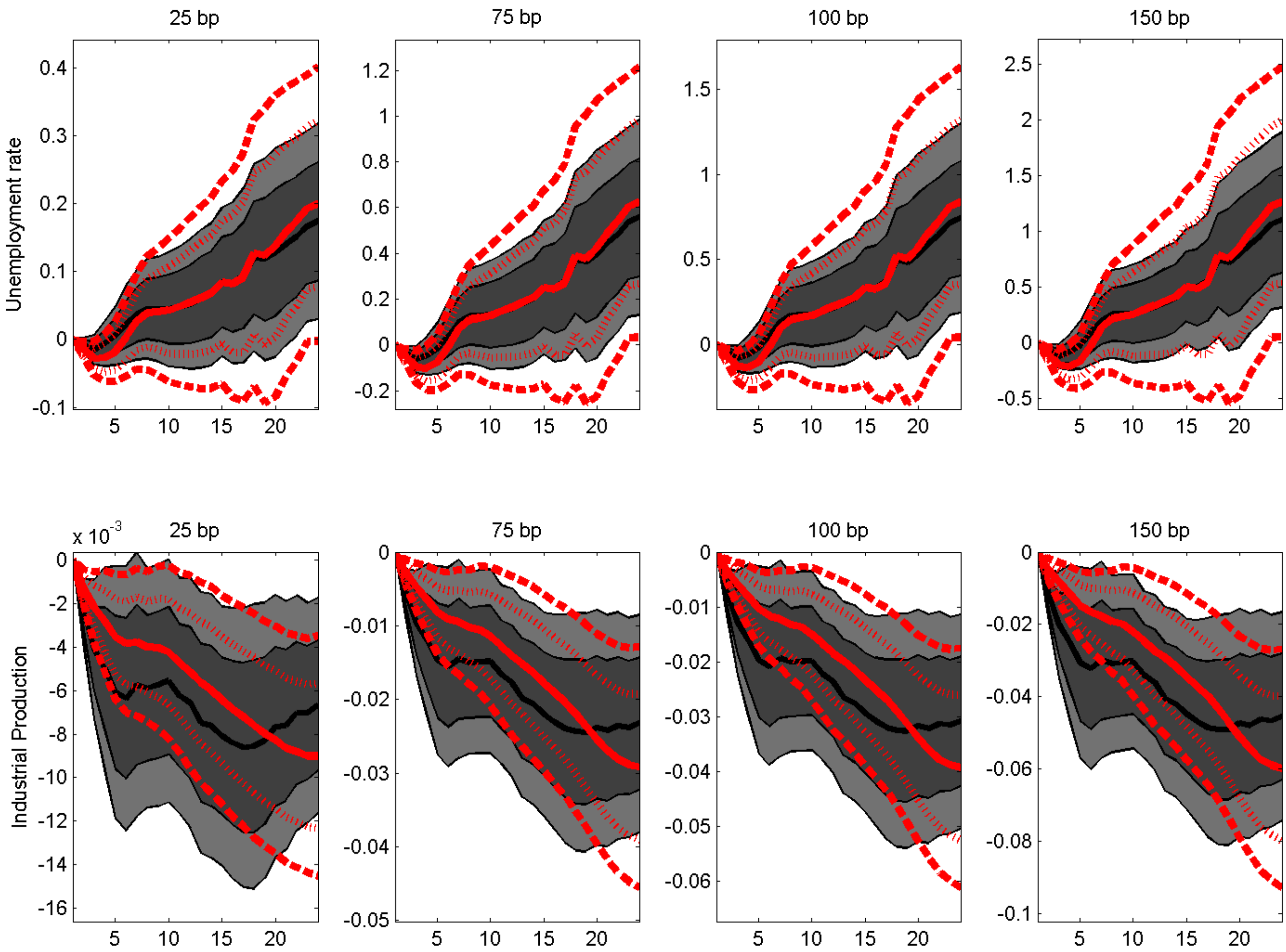


Figure B-3: Euro Area, IRF to a NFC spread shock (Local peak = 12).



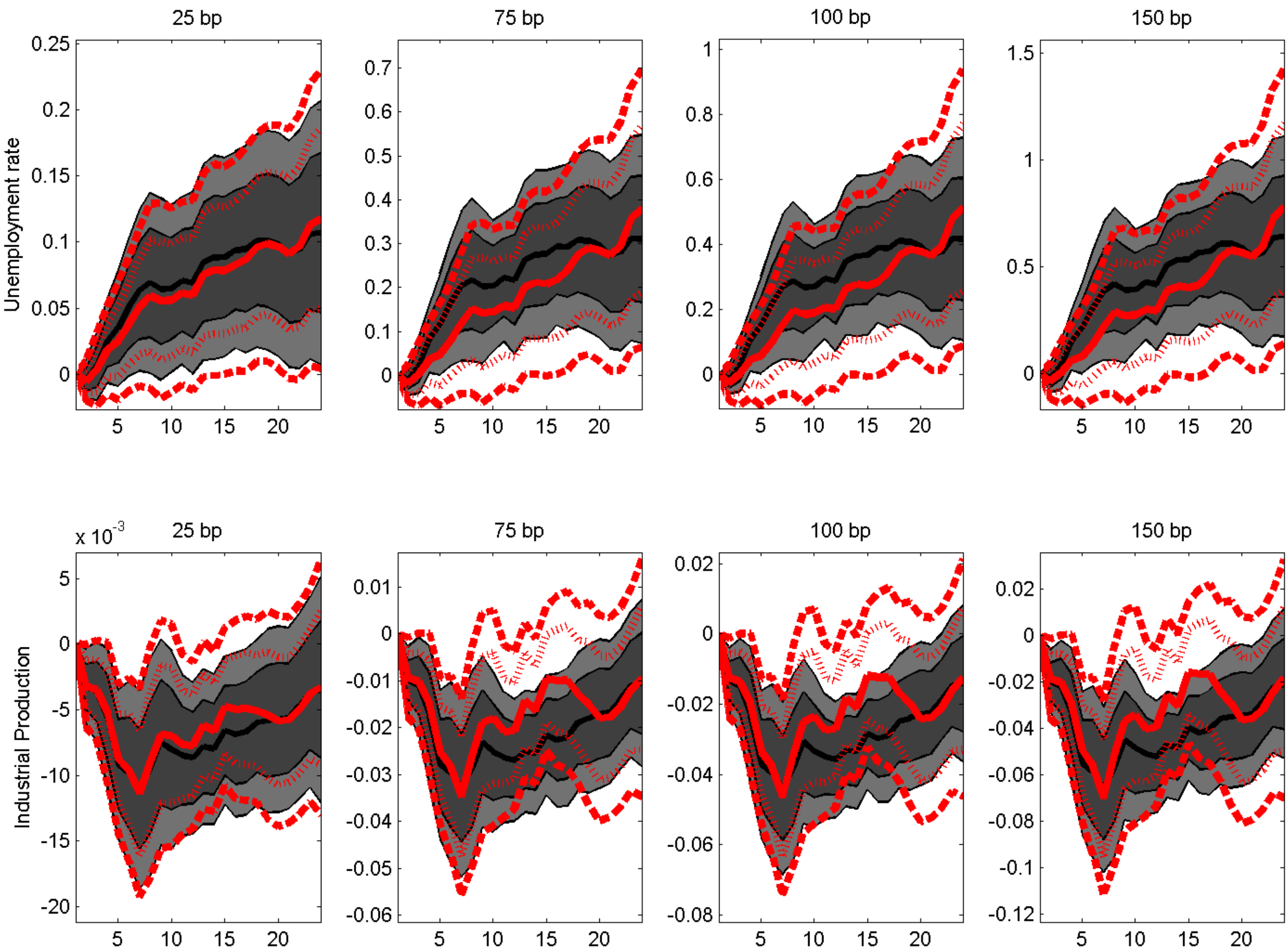
Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1999:01 - 2014:08.

Figure B-4: Euro Area, IRF to a Banking spread shock (Local peak = 12).



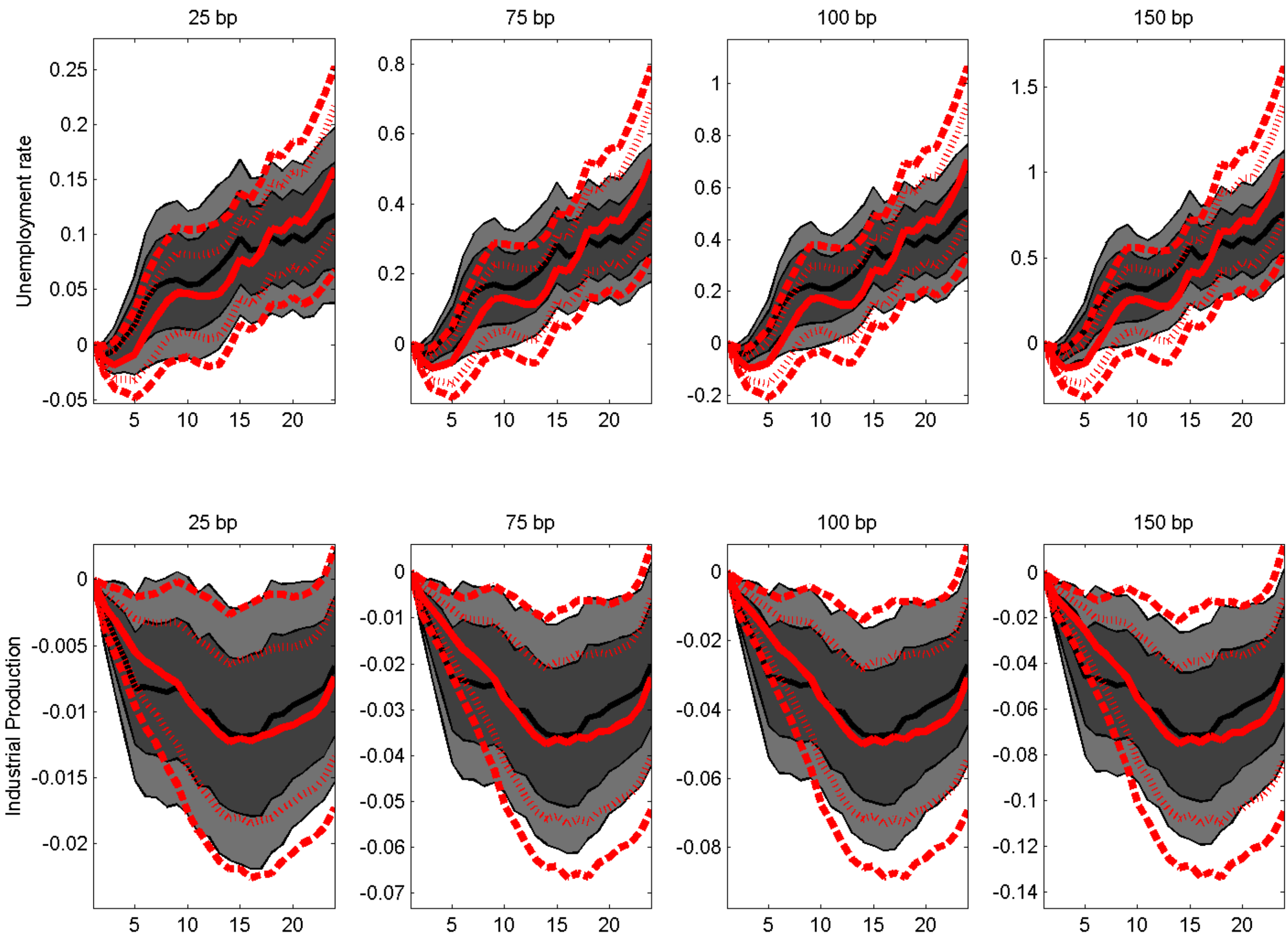
Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 24 months horizon. Sample is 1999:01 - 2014:08.

Figure B-5: France, IRF to a NFC spread shock (Local peak = 12).



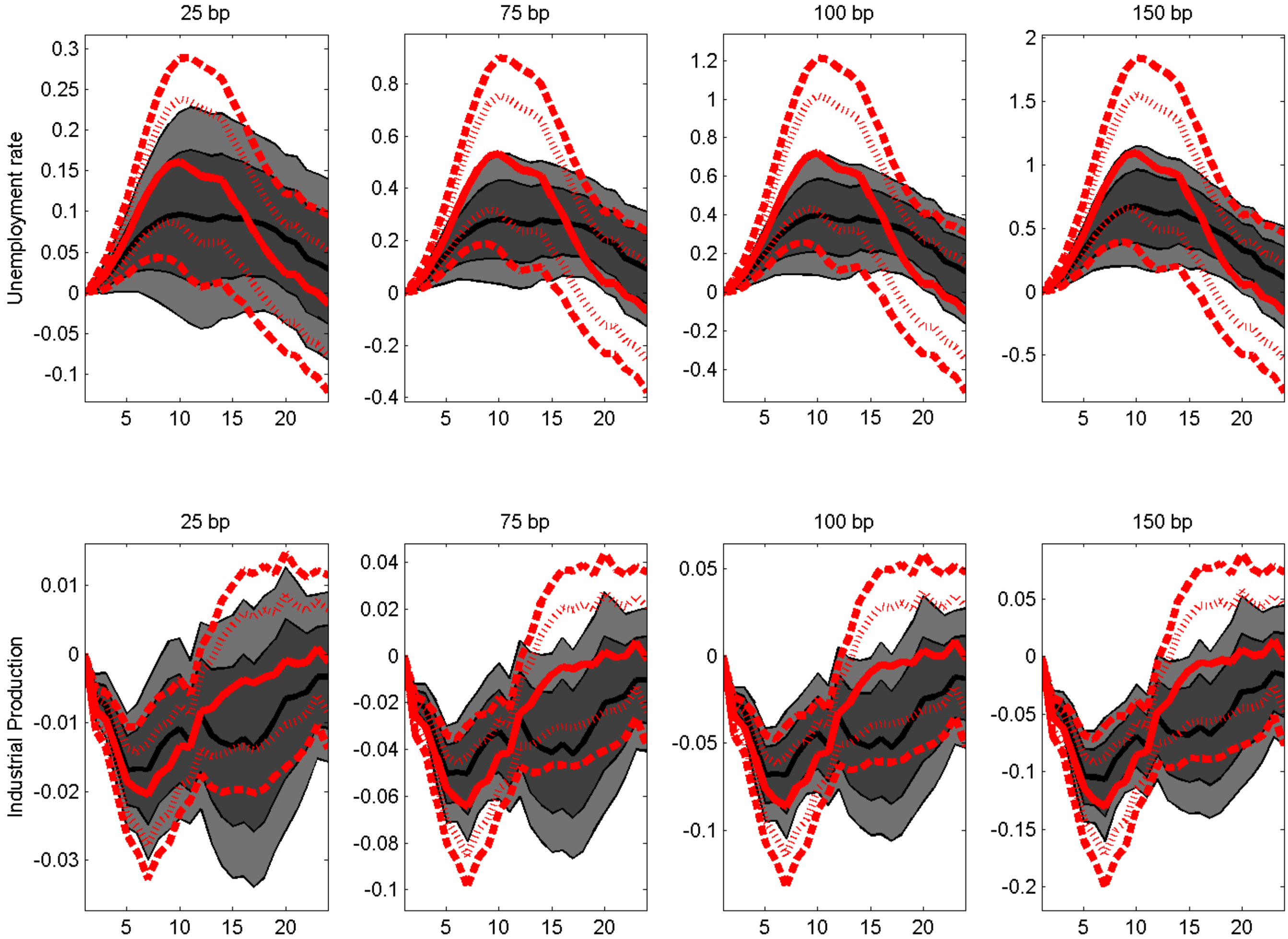
Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1999:01 - 2014:08.

Figure B-6: France, IRF to a Banking spread shock (Local peak = 12).



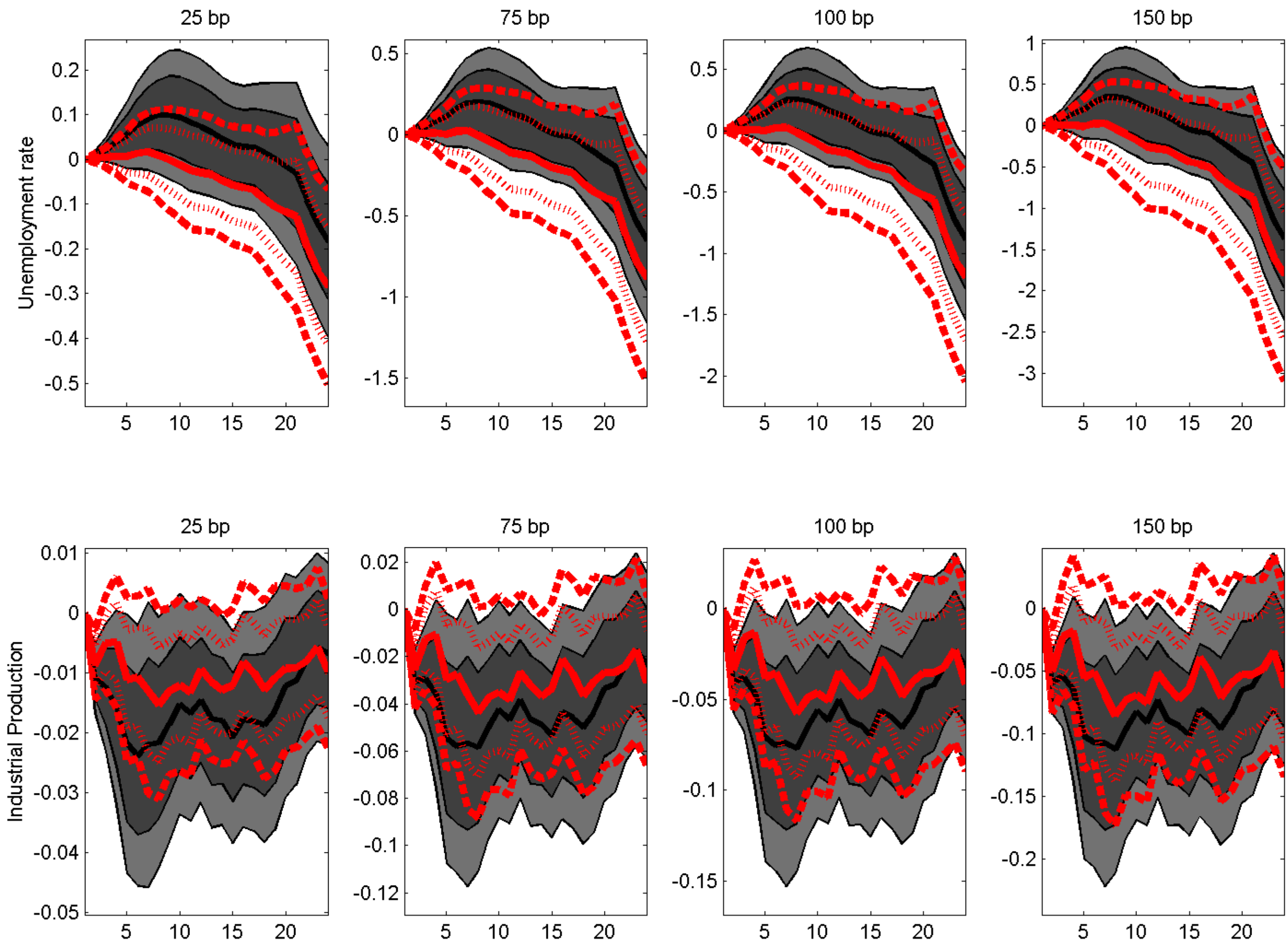
Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 24 months horizon. Sample is 1999:01 - 2014:08.

Figure B-7: Germany, IRF to a NFC spread shock (Local peak = 12).



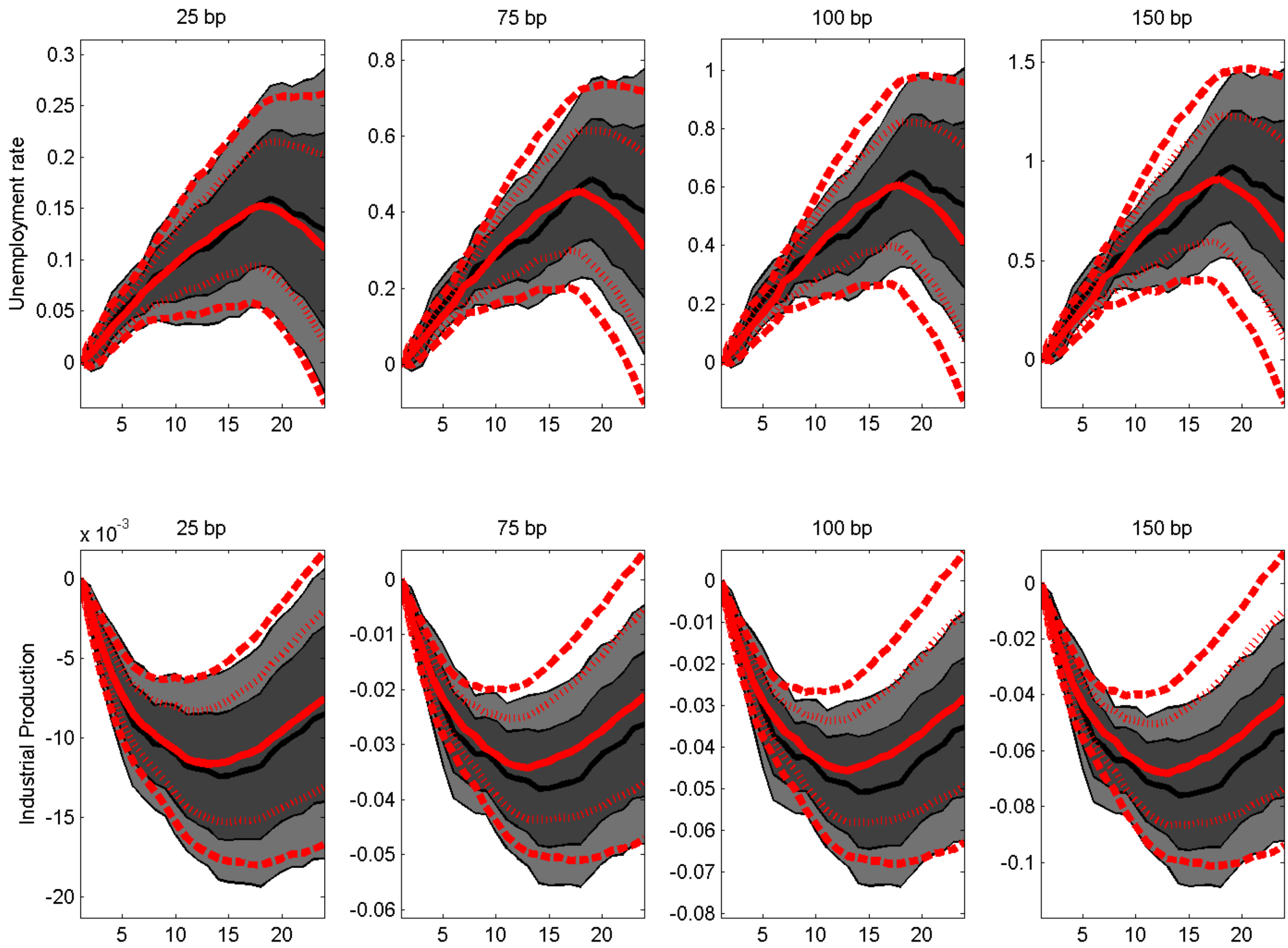
Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1999:01 - 2014:08.

Figure B-8: Germany, IRF to a Banking spread shock (Local peak = 12).



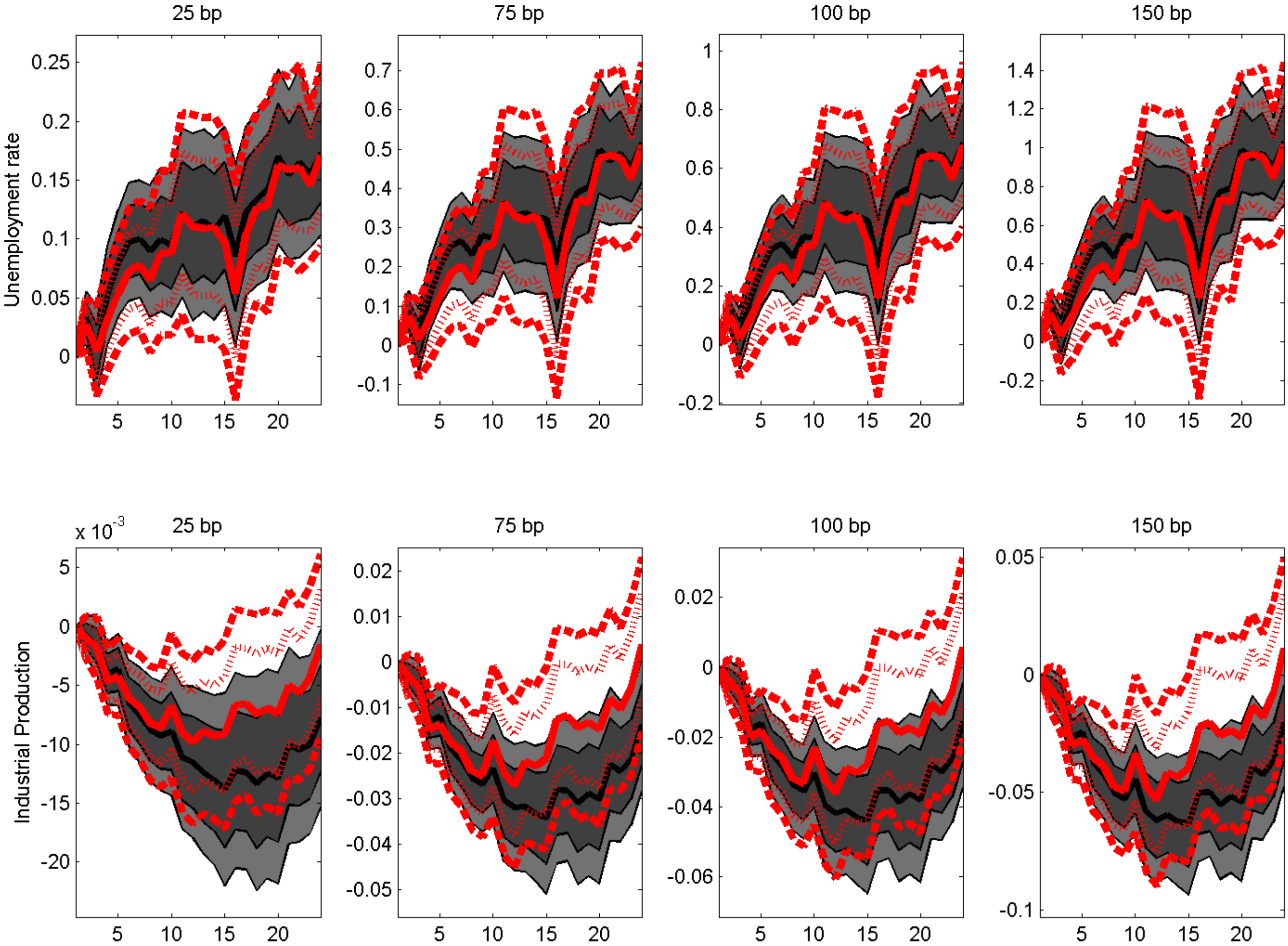
Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 24 months horizon. Sample is 1999:01 - 2014:08.

Figure B-9: Italy, IRF to a NFC spread shock (Local peak = 12).



Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 12 months horizon. Sample is 1999:01 - 2014:08.

Figure B-10: Italy, IRF to a Banking spread shock (Local peak = 12).



Notes: The dark black line represents the estimated median impulse response to a positive shock, i.e. an *increase* in the spreads, together with its 68% (dark gray shaded area) and its 90% (light grey shaded area). The straight red line represents the estimated median impulse response to a negative shock, i.e., a *decrease* in the spreads, together with its 68% (dotted red lines) and its 90% (dashed red lines). From left to right, responses to shocks of increasing size are plotted. Here we are conditioning on a constant history for the shocked variable and the net increase is computed over a 24 months horizon. Sample is 1999:01 - 2014:08.

C Local projections

According to Jorda (2005) under mild assumptions, a nonlinear time series process y_t can be expressed as a generic function of past shocks v_t

$$y_t = \phi(v_t, v_{t-1}, v_{t-2}, ...) \tag{6}$$

Provided that $\phi(.)$ is well behaved, one can construct a first order Taylor expansion around 0 and then get the equivalent of the Wold representation for the non–linear case, i.e. the Volterra expansion

$$y_t = \Sigma_{i=0}^{\infty}\phi_i v_{t-i} + \Sigma_{i=0}^{\infty}\Sigma_{j=0}^{\infty}\phi_{ij} v_{t-i} v_{t-j} + \Sigma_{i=0}^{\infty}\Sigma_{j=0}^{\infty}\Sigma_{k=0}^{\infty}\phi_{ijk} v_{t-i} v_{t-j} v_{t-k} + ... \tag{7}$$

where the constant is omitted for simplicity. The previous expression represents the analogous of the Wold decomposition for the non–linear case. Jorda (2005) shows that IRFs h periods ahead can be obtained from direct regressions of y_t on its lags from h onwards. These direct regressions (local projections) are defined as:

$$y_{t+h} = a^h + B_1^h y_t + Q_1^h y_t^2 + C_1^h y_t^3 + B_2^h y_{t-1} + Q_2^h y_{t-1}^2 + C_2^h y_{t-1}^3 + ... + v_{t+h}^h, ..., s = 0, 1, 2, ..., h \tag{8}$$

where Q_j and C_j represent the quadratic and cubic terms, respectively, and cross-products are ignored. The impulse response is derived by taking the difference between the expected value of y_{t+h} conditional on a shock vector d_i and the expectation conditional on d_i being zero.[23] Therefore, the resulting IRF is:

$$\begin{aligned} IRF(t, s, \mathbf{d}_i) &= \left\{\widehat{\mathbf{B}}_1^s(\mathbf{y}_{t-1} + \mathbf{d}_i) + \widehat{\mathbf{Q}}_1^s(\mathbf{y}_{t-1} + \mathbf{d}_i)^2 + \widehat{\mathbf{C}}_1^s(\mathbf{y}_{t-1} + \mathbf{d}_i)^3\right\} + \\ &- \left\{\widehat{\mathbf{B}}_1^s\mathbf{y}_{t-1} + \widehat{\mathbf{Q}}_1^s\mathbf{y}_{t-1}^2 + \widehat{\mathbf{C}}_1^s\mathbf{y}_{t-1}^3\right\} \\ &= \left\{\widehat{\mathbf{B}}_1^s\mathbf{d}_i + \widehat{\mathbf{Q}}_1^s(2\mathbf{y}_{t-1}\mathbf{d}_i + \mathbf{d}_i^2) + \widehat{\mathbf{C}}_1^s(3\mathbf{y}_{t-1}^2\mathbf{d}_i + 3\mathbf{y}_{t-1}\mathbf{d}_i^2 + \mathbf{d}_i^3)\right\}, \\ &\quad s = 0, 1, 2, ..., h \end{aligned} \tag{9}$$

[23] Structural identification can be obtained through an impact matrix A_0 such that $v_t = A_0\eta_t$ and η_t are the structural shocks.

Ignoring quadratic and cubic terms, but considering that we also have *local peak* terms, leads to the following expression:

$$
\begin{aligned}
IRF(t,s,\mathbf{d}_i) &= \left\{\widehat{\mathbf{B}}_1^s(\mathbf{y}_{t-1}+\mathbf{d}_i)+\widehat{\mathbf{\Theta}}_1^s(\mathbf{y}_{t-1}+\mathbf{d}_i)^+\right\}+ \\
&- \left\{\widehat{\mathbf{B}}_1^s\mathbf{y}_{t-1}+\widehat{\mathbf{\Theta}}_1^s(\mathbf{y}_{t-1})^+\right\} \\
&= \left\{\widehat{\mathbf{B}}_1^s\mathbf{d}_i+\widehat{\mathbf{\Theta}}_1^s[(\mathbf{y}_{t-1}+\mathbf{d}_i)^+-(\mathbf{y}_{t-1})^+]\right\}, \\
& \quad s=0,1,2,...,h
\end{aligned} \tag{10}
$$

corresponding to the one that appears in the main text.