IDENTIFICATION OF SIGN-DEPENDENCY OF IMPULSE RESPONSES

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Discussion Paper No. 19-07

September 2019

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Identification of Sign-Dependency of Impulse Responses*

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September 26, 2019

Abstract

The potential asymmetry of impulse responses to macroeconomic shocks, i.e., the possibility that the economy responds differently to positive and negative shocks, has received increased attention recently. I argue, both analytically and through Monte Carlo simulations, that estimating potential asymmetries by positing a dichotomous moving average (MA) representation that explicitly distinguishes between the MA coefficients on the basis of the shock realizations' sign yields biased estimates of true asymmetry. By contrast, estimating a second-order polynomial in the shock that explicitly models its second-order effect is able to produce unbiased estimates of true asymmetry. Applying the latter specification to study the empirical asymmetries in the economy's response to credit supply and monetary policy shocks, I find response asymmetries that are much smaller than those obtained from the dichotomous specification but that are still significant and economically interesting. Financial frictions seem to be an important amplification mechanism driving these asymmetries.

JEL classification: E32

Key words: Sign-dependency of impulse responses, Local projections, Second-order specification, Dichotomous specification

*I am grateful to Christian Matthes for helpful comments and suggestions.

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1 Introduction

Much of macroeconomic research, both theoretical and empirical, has traditionally focused on frameworks where macroeconomic shocks induce symmetric effects on the economy, i.e., positive and negative shocks produce the same effect (in absolute terms). However, from a theoretical standpoint, this need not be the case as downward nominal wage rigidity (see, e.g., Kim and Ruge-Murcia (2009) and Schmitt-Grohé and Uribe (2016)), financial frictions (see, e.g., Ordoez (2013) and Guerrieri and Iacoviello (2017)), and incomplete markets (see, e.g., Cao and Nie (2017)) all constitute reasonable mechanisms capable of producing sign-dependent effects of macroeconomic shocks.

Importantly, ascertaining the extent of such sign-dependency is valuable not only from an intellectual curiosity standpoint but also from a policymaking one. And this has accordingly prompted empirical research aimed at quantifying the response asymmetry of the economy to various macroeconomic shocks, including monetary policy shocks (see, e.g., Cover (1992), Tenreyro and Thwaites (2016), and Barnichon and Matthes (2018a)), credit supply shocks (see, e.g., Barnichon et al. (2018)), fiscal policy shocks (see, e.g., Barnichon and Matthes (2018b)), and oil shocks (see, e.g., Mork (1989) and Kilian and Vigfusson (2011)).

What This Paper Does. The specification underlying the vast majority of the empirical evidence from the literature on impulse response sign-dependency assumes the economy is represented by a moving average (MA) process that explicitly distinguishes between the MA coefficients on the basis of the shock realizations' sign. Such a dichotomous specification, while allowing for the direct estimation and comparison of impulse responses to positive and negative shocks, is not consistent with the notion that the true data generating process (DGP) implied by a wide class of DSGE models is a multivariate polynomial (of potentially infinite degree) in current and past structural shocks' realizations (see, e.g., Lan and Meyer-Gohde (2013)).

This paper sets out to accomplish two goals. The first is to ascertain the implications of this inconsistency between the usual specification assumed by the literature and the DSGE-implied one and those of correctly using a simple estimation approach that eliminates this inconsistency for

the proper identification of impulse response sign-dependency. To accomplish this, I show both analytically as well as through as Monte Carlo evidence that this inconsistency results in a sizable bias which is completely eliminated by estimation a simple second-order polynomial in the shock of interest. The second is to shed light on how these two estimation approaches differ in terms of the results they produce when applied to actual data and, importantly, what the correct second-order specification teaches us about impulse response sign dependency in the data. Toward this end, I apply these two estimation approaches to actual data and two commonly studied shocks in credit supply and monetary policy shocks and show a quantitatively important discrepancy in economic activity's response asymmetries estimated from these two approaches. Then, I conduct a deeper investigation into the mechanism driving the observed response asymmetries for economic activity by looking at the sign-dependent responses of various structurally informative variables.

In accomplishing the two above-mentioned goals, this paper effectively unfolds in two separate but related parts whose results can be summarized as follows. In relation to the first part, it is first shown analytically that incorrectly estimating a dichotomous specification when the true DGP is a second-order polynomial MA process results in an upward bias in the estimation of the response asymmetry. When the shock of interest is normally distributed, this bias is driven in equal shares by the bias of the positive and negative shocks' effects. However, positive (negative) skewness of the shock distribution causes a larger bias for the estimated effects of the positive (negative) shock and excessive kurtosis increases the overall bias of the estimated response asymmetry by enlarging the bias of both shocks' effects. This result is illustrated numerically by drawing a shock from a random distribution whose skewness and kurtosis match those of an empirical distribution of credit supply shocks. Since credit supply shocks in the data posses moderately negative skewness and significantly excessive kurtosis, the numerical experiment using these empirical higher moments implies a very large asymptotic bias in the estimation of the response asymmetry.

With these analytical and numerical results in mind, I then turn to running suitable Monte Carlo experiments aimed at quantifying the actual small sample bias that could result from erroneously estimating a dichotomous specification as opposed to estimating the correct, second-order

specification. In these experiments I carry out simulations assuming both normally distributed shocks as well non-normally distributed shocks (again, with higher moments matching credit supply shocks' moments in the data) and demonstrate that the bias from both experiment types is meaningful but that it is much larger when assuming the more realistic, non-normal distribution.

In the second part of the paper, I proceed in two stages. First, I present empirical evidence on the sign-dependency of impulse responses of industrial production to credit supply and monetary policy shocks from the two estimation approaches (i.e., the dichotomous specification based one and the second-order specification based one). The results from this exercise clearly point to very sizable differences between the estimated response asymmetries from these two specifications, with the dichotomous one indicating response asymmetries for the two shocks that are more than 6 times larger than those obtained from the second-order specification. Nevertheless, importantly, the results from the second-order specification still indicate a significant response asymmetry with positive (contractionary) credit supply and monetary policy shocks inducing declines in industrial production that are roughly 0.4%-0.5% higher in absolute terms than the corresponding rise in this variable due to negative (expansionary) ones.

Second, I turn to focus on underpinning the structural mechanism underlying the significant response asymmetry estimates from the second-order specification by examining the sign-dependent responses of various structurally informative variables, including the federal funds rate, the nominal hourly wags, credit spreads, and non-financial leverage. The main takeaway message from these results is that downward nominal wage rigidity seems to be a relevant mechanism only for the asymmetric effects of monetary policy shocks, whereas a financial frictions based mechanism seems to be relevant for both credit supply shocks and monetary policy shocks with contractionary shocks appearing to generate stronger intensification of financial frictions than the alleviation of these frictions induced by expansionary shocks.

Notably, for credit supply shocks, there also seems to be a contemporaneous, exogenous sign-dependent mechanism partly driving the results whereby an initial contractionary shock translates into a larger impact rise in its associated fundamental (i.e., the excess bond premium) that the corresponding decline induced by an expansionary shock. This contemporaneous mechanism is allowed for by the way I identify credit supply shocks, as explained in Section 3 on Page 15, and

can be viewed as initial bad shocks to credit markets' risk appetite having a bigger ultimate effect on this appetite within the month in which the shock takes place than the corresponding good-shock-induced effect. Nevertheless, the response asymmetry for industrial production is much more persistent than that for the excess bond premium, indicating that there must an additional mechanism underlying the results other than the asymmetric behavior of risk appetite. And the results for credit spreads and non-financial leverage support the notion that this mechanism is rooted in intensified financial frictions in response to positive credit supply shocks.

Related Literature. Motivated by the asymmetry in business cycles observed in the data and the desire to study potential mechanisms capable of explaining this asymmetry, a fairly large theoretical literature on impulse response sign-dependency has emerged in the last 20 years or so. Chalkley and Lee (1998) and Nieuwerburgh and Veldkamp (2006) suggest a learning-based mechanism where contractionary shocks take place in a boom environment characterized by more forecast precision and thus produce a sharper decline in economic activity than the corresponding more gradual rise induced by expansionary shocks. Occasionally binding constraints on production capacity (Gilchrist and Williams (2000) and Hansen and Prescott (2005)) as well as borrowing capacity (Kocherlakota et al. (2000), Mendoza (2010), and Guerrieri and Iacoviello (2017)) have also been studied as viable asymmetry-producing mechanisms, as in these frameworks contractionary shocks induce bigger effects on the economy by making these constraints slack whereas expansionary shocks make them bind thus limiting the resulting economic expansion. Interestingly, Cao and Nie (2017) have recently argued that borrowing constraints' asymmetric amplification effects vanish once complete markets with fully state contingent assets are assumed, meaning that incomplete markets constitute an important source of impulse response sign-dependency. Integrating a learning mechanism with financial frictions captured by bankruptcy costs, Ordoez (2013) builds a model where contractionary shocks generate bigger effects on the economy by intensifying financial frictions which in turn tends to hinder the flow of information more after crises than before crises, thus inducing stronger asymmetries. Finally, several works have focused on asymmetry-producing mechanisms rooted in the labor market, including asymmetric adjustment costs on employment (McKay and Reis (2008)) and asymmetric wage rigidity (Kim and Ruge-Murcia (2009),

Abbritti and Fahr (2013), Schmitt-Grohé and Uribe (2013, 2014, 2016), and Aruoba et al. (2017)).

The empirical literature on impulse response sign-dependency to which my paper belongs can be divided into three strands. Before proceeding with my discussion of these strands, I note that I am making a distinction between the literature on impulse response sign-dependency and the larger one on impulse response state-dependency and confine myself to discussing the former given the sole focus of this paper on impulse response sign-dependency.[1]

The first strand consists of works using threshold models to estimate asymmetric impulse responses where the asymmetry can originate from the "switching variable" (e.g., past output growth or unemployment) to which the threshold applies and according to which positive and negative shocks' effects are allowed to vary (through changes in the model's reduced form coefficients). Papers using threshold models have usually found significant impulse response sign-dependence (see, e.g., Beaudry and Koop (1993), Thoma (1994), Potter (1995), Koop et al. (1996), Ravn et al. (1996); Ravn and Sola (2004), Weise (1999), Holmes and Wang (2002), Lo and Piger (2005), and Rahman and Serletis (2010)). Nevertheless, as explained in Barnichon and Matthes (2018a), because the switching variable is the not the structural shock of interest but rather some endogenous variable which is itself a function of various past structural shocks, there is no "right" switching variable and accordingly results tend to be sensitive to the choice of this variable.

The second strand includes works that, conditional on having some identified structural shock at hand, use straightforward regression techniques to estimate regressions of an outcome variable of interest on current and past values of positive and negative realizations of this shock. This estimation approach has been mainly applied to monetary policy shocks obtained as residuals from an estimated money supply process (see, e.g., De Long et al. (1988), Cover (1992), and Morgan (1993)), generally finding that contractionary policy shocks induce bigger output effects than ex-

[1] Although some overlap exists between the two with some papers empirically studying both sign-dependency and state-dependency of impulse responses to macroeconomic shocks with roughly even focus, there is a fairly large number of papers whose focal point is the state-dependent nature of shocks rather than their sign-dependent nature. One notable example of a paper belonging to the former group of papers is Tenreyro and Thwaites (2016), who examine both state-dependency of monetary policy shocks' effects with the states being expansions and recessions as well as their sign-dependency; one notable sub-group belonging to the latter group is the one on fiscal multipliers' state-dependence (see, e.g., Auerbach and Gorodnichenko (2012a,b), Ilzetzki et al. (2013), Owyang et al. (2013), and Ramey and Zubairy (2018)).

pansionary ones.[2] Two shortcomings of this estimation approach are that the monetary policy shock series may suffer from misidentification and that sizable efficiency loss can arise from the fact that the number of lags included in the regression needs to match the horizon up to which the output response is estimated. More recently, Tenreyro and Thwaites (2016) included current positive and negative realizations of the narratively identified monetary shock series from Romer and Romer (2004) in local projection (LP) regressions (Jorda (2005)) to estimate sign-dependant impulse responses, also finding larger effects for contractionary shocks.[3] The narrative approach facilitates overcoming the first above-mentioned disadvantage whereas the LP framework helps to alleviate the efficiency issue by allowing to include only the contemporaneous positive and negative shock values in each rolling regression of the LP framework.

The third strand of the literature concerns the "Functional Approximation of Impulse Responses" (FAIR) method introduced by Barnichon and Matthes (2018a) as a general method for estimating impulse responses by approximating impulse responses with a set of basis functions. There can be various specific implementations of the FAIR method, including estimation of linear impulse responses, size-dependency of impulse responses, as well as the specific implementation relevant for my paper which is impulse response sign-dependency. Much like the second strand of the literature, this implementation also assumes a dichotomous DGP where endogenous variables of interest are represented by an MA decomposition in terms of positive and negative realizations of a shock of interest with potentially different MA coefficients on these realizations. However, importantly, it provides a novel and appealing estimation method for identifying asymmetry when

[2]In accordance with early evidence from Mork (1989) that oil price declines have insignificant effects on output that are much smaller than the significant negative output effects induced by oil price increases, the oil shocks literature has commonly assumed that only oil price increases matter and thus has tended to include a variable in the VAR that captures increases but not decreases (see, e.g., Hamilton (1996), Bernanke et al. (1997), Davis and Haltiwanger (2001), Lee and Ni (2002), and Ramey and Vine (2011)). Nevertheless, Kilian and Vigfusson (2011) demonstrate the serious biases and erroneous inference that can result from this specification. Putting forward an econometric model that encompasses both symmetric and asymmetric models as special cases by also accounting for the presence of oil price decreases, Kilian and Vigfusson (2011) are able to correct for this omitted variable driven bias and show that correctly computed impulse responses to positive and negative oil shocks do not point to significant asymmetry.

[3]In the context of fiscal shocks, Brinca et al. (2019) find that the fiscal multiplier is increasing in the spending shocks by instrumenting for government spending with positive and negative realizations of the shock from Blanchard and Perotti (2002) and the narratively identified shock from Ramey (2011) in LP regressions of output on government spending where sign-dependent multipliers were obtained by pooling observations across periods with negative and positive fiscal shocks.

one does not observe the shock of interest but instead needs to identify it in an internally consistent manner using suitable identifying restrictions. In addition to the efficiency gain from using the FAIR method owing to the strong dynamic restrictions it imposes between the parameters of the impulse response function, this serves as the main advantage of the FAIR method relative to straightforward estimation techniques of asymmetric impulse responses such as the LP framework which require an observed shock of interest. The implementation of the FAIR method for response asymmetry estimation has been applied to monetary policy shocks (Barnichon and Matthes (2018a)), fiscal policy shocks (Barnichon and Matthes (2018b)), and credit supply shocks (Barnichon et al. (2018)), all finding significantly larger effect of contractionary shocks.

Contribution to Literature. The contribution of my paper to the above-cited empirical literature is twofold. First, I highlight that the assumed DGP underlying the second and third strands of this literature is misspecified and that this misspecification can lead to severe bias. Since the first strand also effectively suffers from a misspecification problem (given the switching variable not being the shock of interest), this first contribution is also relevant for the threshold models part of the literature. Second, having at hand an unbiased and straightforward estimation approach, I conduct an investigation into not only the asymmetry in real activity's response to commonly studied shocks (i.e., credit supply and monetary policy shocks), but also into the candidate mechanisms emphasized by theoretical models for underlying this asymmetry. Such structurally informative evidence has been somewhat missing from the empirical literature and my analysis aims to fill this gap.

Importantly, I conduct the analysis of this paper on the premise that the shock of interest is observed or can be properly identified separately and then used for the LP-based estimation of impulse response sign-dependency (as in Tenreyro and Thwaites (2016)). As noted above with respect to the FAIR method, the fact that this assumption need not be made for the latter method serves as its arguably most notable advantage over the LP-based approach (in addition to the efficiency gain from the FAIR method). Nevertheless, as a central aim of this paper is to isolate and stress the biasing role of the misspecification encapsulated in the dichotomous specification, I abstract from the issue of shock identification uncertainty altogether and effectively take the

identified shock as given.[4]

Outline. The remainder of the paper is organized as follows. In the next section I lay out the details of the underlying framework of this paper and also provide analytical evidence on the bias resulting from the dichotomous specification. Section 3 provides Monte Carlo evidence on this bias using suitable simulation experiments. Section 4 begins with a description of the data, after which it presents the main empirical evidence. Section 6 discusses the validity of the interpretation of this paper's results on credit supply shocks in relation to the asymmetric response of EBP. The final section concludes.

2 Underlying Framework

Prior to presenting the dichotomous specification and its associated estimation bias, I first explain the theory-consistent DGP assumed in the analysis employed in this paper.

2.1 Theory-Consistent DGP

To fix ideas and form a suitable conceptual base for my analysis, I begin with a clear definition of impulse response sign-dependency. Toward this end, consider a general data generating process (DGP) for an endogenous variable of interest y_t (say, logged industrial production) as implied by

[4]One can argue that this approach, while suitable for stressing the above-mentioned biasing role, may underestimate the confidence intervals in the empirical analysis part of the paper that deals with credit supply shocks as it does not account for uncertainty in the identification procedure used to extract these shocks. I have confirmed that the inference drawn in the empirical analysis regarding the asymmetric effects of credit supply shocks is robust to using a suitable Bayesian estimation and inference framework that accounts for shock identification uncertainty. That said, as explained above, I abstract from shock identification uncertainty to keep with the central theme of this paper and to maintain a coherent analysis throughout the paper.

a wide class of DSGE models (see, e.g., Lan and Meyer-Gohde (2013)):[5]

$$y_t \quad = \quad \gamma t + \sum_{i=0}^{\infty} \alpha_i \epsilon_{t-i} + \sum_{j=0}^{\infty} \sum_{i=0}^{\infty} \beta_{j,i} (\epsilon_{t-j} \otimes \epsilon_{t-i}), \tag{1}$$

where γ is the stochastic steady state growth rate of y_t, i.e., the growth rate that y_t would obtain in the presence of uncertainty regarding future shocks and zero shock realizations up to period t; ϵ_t is a $k \times 1$ vector of economic, white noise shocks; α_i's are the $1 \times k$ first-order moving average (MA) coefficients of the MA process from Equation (1); $\beta_{j,i}$'s are the $k \times k$ second-order MA coefficients; and $\otimes$ is the Kronecker product.

While MA Process (1) is accurate only up to a second-order approximation, this level of accuracy is sufficient for my purposes given that sign-dependency of impulse responses can be straightforwardly incorporated and defined via the second-order terms from Equation (1). Specifically, assuming our shock of interest is the first element of ϵ_t (ϵ_t^1) and that we are interested in identifying its effect on y_t h periods ahead conditional on the economy being in a stochastic steady state in period t (i.e., no shocks have hit the economy until period t), our theoretical object of interest can be computed as

$$\frac{\partial y_{t+h}}{\partial \epsilon_t^1} \Delta \epsilon_t^1 + \frac{1}{2} \frac{\partial^2 y_{t+h}}{\partial (\epsilon_t^1)^2} \Delta (\epsilon_t^1)^2 \;\Big|\; \left\{ \forall i > 0, \forall j,\ \epsilon_{t-i}^j = 0 \,; \forall j > 1,\ \epsilon_t^j = 0 \right\} = \alpha_h^1 \epsilon_t^1 + \frac{1}{2} \beta_{h,h}^{1,1} (\epsilon_t^1)^2, \tag{2}$$

where α_h^1 is the first element of first-order coefficient vector α_h and $\beta_{h,h}^{1,1}$ the $(1,1)$ element of second-order coefficient matrix $\beta_{h,h}$. Note that the impulse response object from (2) corresponds to the

[5]For models with occasionally binding constraints (OBCs), which arise in many economic applications and constitute an important part of the theoretical macroeconomics literature, it is in general not necessarily the case that a smooth approximation such as (1) would provide a sufficiently precise representation of their solution. The reason for this is that perturbation-based methods would generally lead to violation of the constraints. However, in practice, macroeconomic models containing such constraints have been found to be well approximated by perturbation-based methods. Guerrieri and Iacoviello (2015) develop a piecewise perturbation approach that gives a good approximation to the solution of these models. In a more recent paper, Holden (2016) develops an accurate and fast perturbation-based-algorithm that first solves the model via perturbation techniques while ignoring the potential violation of the constraints, and then imposes the constraints' bounds by adding endogenous news shocks that correct for potential violation of these bounds. The method from Holden (2016) improves on the method from Guerrieri and Iacoviello (2015) in being applicable to higher-order pruned perturbation solutions, which is especially relevant for my analysis as it implies that models with OBCs considered in the macroeconomics literature can be reasonably approximated by DGPs of the type encapsulated in (1). This implication is also borne out by recent results from Benigno et al. (2017) and Binning and Maih (2017) which establish the validity of higher-order perturbation-based solutions of models with OBCs via the treatment of the constraints through the lens of an endogenous regime-switching framework.

second-order Taylor expansion around the stochastic steady state of y_{t+h} with respect to a change in ϵ_t^1 and therefore encapsulates sign-dependence owing precisely to the presence of $(\epsilon_t^1)^2$ in it. The main motivation of this paper is to gain a better understanding of the extent to which current results on impulse response asymmetry capture the theoretical object from (2) and what would be the implications of explicitly setting out to identify this object via a simple second-order, quadratic specification in the shock of interest.

Notably, the analysis of this paper is conducted for a *given* shock size (specifically, one standard deviation shock size) for both the positive and negative shock so as to only focus on sign-dependency and leave aside the issue of size-dependency. Formally, the impulse response asymmetry object implied by (2), which is defined as the difference between the effect of a positive shock and that of a negative shock (with the latter shock multiplied by -1 for comparison purposes), is considered on the basis of a one unit change in ϵ_t^1 (with ϵ_t^1 normalized to have unit standard deviation) and is therefore represented by $\beta_{h,h}^{1,1}$, i.e., excluding the unit-sized $(\epsilon_t^1)^2$. While the exclusion of $(\epsilon_t^1)^2$ is merely a result of my chosen normalization of the shock, the more important takeaway from this exposition of the response asymmetry object is that this object is studied for a constant, given shock size for both the positive and the negative shock throughout my analysis. As such, this object of interest abstracts from the issue of size-dependency.[6] More generally, my focus on including only an *even* higher-order power (i.e., 2) in my baseline second-order specification while conditioning the results on a given shock size can serve the purpose of quantifying sign-dependency in parallel to remaining consciously silent on size-dependency.

I now proceed to discussing what econometric framework is usually used in the literature to meet the challenge of identifying the object from (2) and why this framework is susceptible to falling short of overcoming this challenge.

[6]Nevertheless, it is worth noting that in my estimations I have also experimented with adding a cubed term of the shock of interest (similar to Tenreyro and Thwaites (2016), although they include only a linear and cubed terms in their cubed-shock-augmented regressions) to inspect the potential effect of shock size on my results and found the coefficient on the cubed term for both credit supply shocks and monetary policy shocks to be insignificant.

2.2 Dichotomous DGP

Much of the recent literature on asymmetric effects of macroeconomic shocks has assumed a dichotomous DGP, where endogenous variables of interest are represented by a moving average decomposition in terms of positive and negative realizations of a shock of interest with potentially different MA coefficients on these realizations (see, e.g., Tenreyro and Thwaites (2016), Barnichon and Matthes (2018a,b), and Barnichon et al. (2018)). In particular, continuing with the denotation of the shock of interest as ϵ_t^1, this type of dichotomous DGP can be written as

$$y_t \quad = \quad \gamma t + \sum_{i=0}^{\infty} b_i^+ \epsilon_{t-i}^{1,+} + \sum_{i=0}^{\infty} b_i^- \epsilon_{t-i}^{1,-} + u_t, \tag{3}$$

where $\epsilon_t^{1,+} = max[0, \epsilon_t^1]$ and $\epsilon_t^{1,-} = min[0, \epsilon_t^1]$; b_i^+'s and b_i^-'s are the MA coefficients (impulse responses) corresponding to positive and negative shock realizations, respectively; and u_t represents the contribution of all other shocks (i.e., $\epsilon_t^2, \epsilon_t^3, ..., \epsilon_t^k$).

Conditional on observing ϵ_t^1, an econometrician interested in estimating MA coefficients b_i^+ and b_i^- can go about this using standard techniques, the most straightforward one being the local projection (LP) model from Jorda (2005). An alternative, much more intricate estimation approach introduced by Barnichon and Matthes (2018a), termed "Functional Approximation of Impulse Responses" (FAIR), estimates the moving average representation of the data by approximating impulse responses with a set of basis functions and provides a novel and appealing estimation method for identifying asymmetry when one does not observe ϵ_t^1. Nevertheless, I proceed with my analysis using the LP estimation approach for two reasons. First, since this paper's aim is to isolate as cleanly as possible the biasing role of erroneously assuming the dichotomous DGP from Equation (3), I prefer to adhere to a conventional and straightforward estimation method that can best facilitate displaying this role. In doing so, I also effectively assume that ϵ_t^1 is observed, which removes the complicated issue of how to identify ϵ_t^1 itself and thus better moves me toward accomplishing my aforementioned aim. Second, since the FAIR approach and the LP one have produced similar results concerning asymmetry for the three macroeconomic shocks investigated using FAIR,[7] there is reason to believe that the underlying DGP assumed in the works using these

[7] Tenreyro and Thwaites (2016) found larger effects of contractionary monetary policy shocks using the LP approach as did Barnichon and Matthes (2018a) using the FAIR approach; and Barnichon and Matthes

two approaches has common implications for their associated results thus limiting the loss of generality from my focusing only on the LP approach.

Estimation Bias. The question that begs from the discussion in this Section and that from the previous one is what meaningful bias, if any, can result from estimating Equation (3) when the true equation generating the data is Equation (1). To make the two equations more comparable, let us write Equation (1) explicitly in terms of ϵ_t^1 as follows:

$$y_t = \gamma t + \sum_{i=0}^{\infty} \alpha_i^1 \epsilon_{t-i}^1 + \sum_{i=0}^{\infty} \beta_{i,i}^{1,1} (\epsilon_{t-i}^1)^2 + v_t, \tag{4}$$

where α_i^1 and $\beta_{i,i}^{1,1}$ represent the first- and second-order MA coefficients with respect to ϵ_{t-i}^1 and $\epsilon_{t-i}^1)^2$, respectively; and v_t represents the remaining first- and second-order contributions of all other shocks. As currently written, the residuals in both Equation (3) (u_t) and Equation (4) (v_t), while independent of the observed shock ϵ_{t-i}^1, are potentially non-stationary and thus make standard LP-based OLS estimation and inference inapplicable. Hence, with the aim of resolving this issue and facilitate the applicability of standard OLS estimation techniques, let us move y_t from Equations (3) and (4) h periods forward and subtract from the resulting time-forwarded MA processes Equations (3) and (4) to obtain

$$\begin{aligned} y_{t+h} - y_t &= \gamma h + \sum_{i=0}^{t+h-1} b_i^+ \epsilon_{t+h-i}^{1,+} + \sum_{i=0}^{t+h-1} b_i^- \epsilon_{t+h-i}^{1,-} + \qquad (5) \\ &+ \sum_{i=0}^{\infty} (b_{i+h}^+ - b_i^+) \epsilon_{t-i}^{1,+} + \sum_{i=0}^{\infty} (b_{i+h}^- - b_i^-) \epsilon_{t-i}^{1,-} + u_{t+h} - u_t, \\ y_{t+h} - y_t &= \gamma h + \sum_{i=0}^{t+h-1} \alpha_i^1 \epsilon_{t+h-i}^1 + \sum_{i=0}^{t+h-1} \beta_{i,i}^{1,1} (\epsilon_{t+h-i}^1)^2 + \qquad (6) \\ &+ \sum_{i=0}^{\infty} (\alpha_{i+h}^1 - \alpha_i^1) \epsilon_{t-i}^1 + \sum_{i=0}^{\infty} (\beta_{i+h,i+h}^{1,1} - \beta_{i,i}^{1,1}) (\epsilon_{t-i}^1)^2 + v_{t+h} - v_t. \end{aligned}$$

Note that the stationarity of Processes (5) and (6) is ensured by the fact that $\lim_{i\to\infty} b_{i+h}^+ - b_i^+ = \lim_{i\to\infty} b_{i+h}^- - b_i^- = 0$ and $\lim_{i\to\infty} \alpha_{i+h}^1 - \alpha_i^1 = \lim_{i\to\infty} \beta_{i+h,i+h}^{1,1} - \beta_{i,i}^{1,1} = 0$, respectively, which in turn makes

(2018b) and Barnichon et al. (2018) demonstrate that similar results on asymmetry is obtained from using these two estimation approaches for fiscal policy shocks and credit supply shocks, respectively. (More precisely, Barnichon and Matthes (2018b) and Barnichon et al. (2018) estimate a hybrid VAR-LP model where the shocks are first identified in a structural VAR and then used in an LP model to identify their effects.)

the Jorda (2005) OLS-based method applicable to both of these equations. The fourth to sixth terms in both equations can be grouped together and denoted by U_{t+h} and V_{t+h}, resulting in the following equivalent and more parsimonious equations:

$$y_{t+h} - y_t = \gamma h + \sum_{i=0}^{t+j-1} b_i^+ \epsilon_{t+j-i}^{1,+} + \sum_{i=0}^{t+j-1} b_i^- \epsilon_{t+j-i}^{1,-} + U_{t+h}, \tag{7}$$

$$y_{t+h} - y_t = \gamma h + \sum_{i=0}^{t+h-1} \alpha_i^1 \epsilon_{t+h-i}^1 + \sum_{i=0}^{t+h-1} \beta_{i,i}^{1,1} (\epsilon_{t+h-i}^1)^2 + V_{t+h}. \tag{8}$$

What bias, if any, would result from estimating Equation (7) via an LP regression framework when the true DGP is (8)? To answer this question, let us first write these equations in matrix notation as follows:

$$Y_h = X_h B_h + U_h, \tag{9}$$

$$Y_h = X_h A_h + \Xi_h \beta_{h,h}^{1,1} + V_h, \tag{10}$$

where h is the rolling horizon; $Y_{i,h} = [y_{i,h+1} - y_{i,1}, y_{i,h+2} - y_{i,2}, ..., y_{i,T} - y_{i,T-h-1}]'$, with T being the length of the sample; $X_h = [X_2, ..., X_{T-h}]'$, with $X_t = [1, \epsilon_t^{1,+}, \epsilon_t^{1,-}]'$; $B_h = [\gamma h, b_h^+, b_h^-]$; $A_h = [\gamma h, \alpha_h^1, \alpha_h^1]$; $\Xi_h = [(\epsilon_2^1)^2, ..., (\epsilon_{T-h}^1)^2]'$; and $U_h = [u_{h+1}, ..., u_T]'$ and $V_h = [v_{h+1}, ..., v_T]'$.

Combining Equation (10) with the standard OLS estimate formula for B_h ($\hat{B}_h = [\hat{\gamma}_h, \hat{b}_h^+, \hat{b}_h^-]$), we can derive an expression linking the latter estimate to the true coefficients from Equation (10):

$$\begin{aligned} \hat{B}_h &= (X_h' X_h)^{-1} X_h' Y_h = (X_h' X_h)^{-1} X_h' (X_h A_h + \Xi_h \beta_{h,h}^{1,1} + V_h) = \\ &= A_h + (X'X)^{-1} X' \Xi_h \beta_{h,h}^{1,1} + (X'X)^{-1} X' V. \end{aligned} \tag{11}$$

Taking expectation of Equation (11) gives

$$\mathbb{E}[\hat{B}_h] = A_h + \beta_{h,h}^{1,1} \mathbb{E}\left[(X_h' X_h)^{-1} X_h' \Xi_h \right], \tag{12}$$

where the term relating to V_h has now vanished owing to its orthogonality with respect to X_h. Equation (12) delivers the main takeaway of this section: when the true DGP is the nonlinear MA process from (10), applying an LP-based estimation of Equation (9) will produce a bias that depends on how far $(X_h' X_h)^{-1} X_h' \Xi_h$ is from the identity matrix. Notably, there is no apriori reason for this distance to be small and, in fact, it should be quite meaningful in general under standard

assumptions regarding economic shocks' distributions. To get a sense of the asymptotic bias that would result from this estimation, I drew a random variable of length 10^7 from the standard normal distribution and used the resulting series (the proxy for ϵ_t^1) to compute the term $(X_h' X_h)^{-1} X' \Xi_h$ and the associated bias for $\hat{b}_h^+$ and $\hat{b}_h^- I$. The resulting asymptotic bias for these coefficients appears to be very meaningful, amounting to roughly 2.2 times the true coefficient $\beta_{h,h}^{1,1}$. This means that if $\beta_{h,h}^{1,1} = 1$ then asymptotically we would get $\hat{b}_h^+ = 2.2$ and $\hat{b}_h^- = -2.2$, which would in turn lead to a significant upward bias in the assessment of the asymmetry in impulse responses to the shock.

Importantly, the aforementioned bias is equal for positive and negative shocks when the shock is normally distributed as this will make the distance between $(X_h' X_h)^{-1} X_h' \Xi_h$ and the identity matrix symmetric with respect to the sign of the shock. More generally, positive (negative) skewness will increase (decrease) the bias for the positive (negative) shock whereas excess kurtosis will increase the bias for both shocks. Since macroeconomic shocks are usually non-normally distributed, this issue can bear significant implications for the actual bias that results from estimating Equation (9). To illustrate this point, I repeated the same experiment from above but now drawing a random variable from a Pearson distribution that possesses the skewness and kurtosis of the credit supply shock series I shall use in the empirical analysis below (-0.46 and 9.45, respectively). The resulting bias is now much larger for both shocks, and expectedly more so for the negative shock given the negative skewness, with $\hat{b}_h^+ = 3.11$ and $\hat{b}_h^- = -3.79$.

I will return to the role of the shock's distribution in the estimation bias in the next section, where I turn to assess how important this bias is in practical terms for realistic small samples and DGPs by using suitable Monte Carlo experiments for comparing the performance of estimates from estimation of Equation (9) relative to estimation of Equation (10). (It is straightforward to show that standard OLS estimation of Equation (10) yields unbiased estimates of impulse response asymmetry.)

3 Monte Carlo Evidence

Objective. This section aims to provide an assessment of the small sample bias which is likely to result from estimating Equation (9) instead of Equation (10), with the latter assumed to rep-

resent the true DGP in the economy. By using suitable and realistic DGPs in the Monte Carlo experiments, such assessment can serve as a valuable gauge of the actual bias that is likely to emerge from estimation of Equation (9) when using real data.

Experimental Design. The DGP I use in the Monte Carlo experiments is based on Equation (4), which I rewrite here for convenience:

$$y_t = \gamma t + \sum_{i=0}^{\infty} \alpha_i^1 \epsilon_{t-i}^1 + \sum_{i=0}^{\infty} \beta_{i,i}^{1,1} (\epsilon_{t-i}^1)^2 + v_t. \tag{13}$$

As explained above, I place focus on experimenting with realistic as possible DGPs so as to increase the informativeness of my Monte Carlo evidence for gauging the actual bias resulting from estimating Specification (9). To accomplish this, I let the data discipline the DGP from (13) by assigning for γ, α_i^1, and $\beta_{i,i}^{1,1}$ the values estimated from applying an LP-based estimation of Equation (10), where y_t is logged industrial production and ϵ_t^1 is taken as the standardized residual from the following two-step estimation procedure. First, I run a regression of the monthly excess bond premium variable (EBP) from Gilchrist and Zakrajek (2012) on 12 lags of own values and squared values as well as 12 lags of the values and squared values of log-first-differences of real S&P 500 and collect the residual from this regression. Second, I regress this residual on its squared value and define the standardized residual from this regression as the credit supply shock series (denoted by $\hat{\epsilon}_t^1$ for future reference). This is also the credit supply shock series I use in the empirical analysis that follows this section. The second estimation step is meant to alleviate the concern that any contemporaneous, exogenous sign-dependent mechanism (as reflected in terms of squared values of the credit supply shock) linking the credit supply shock and its associated fundamental (i.e., EBP) is significantly biasing my identified credit supply shock series. Indeed, the coefficient from the regression of the second step is positive with a p-value of 6.5%, indicating that there appears to be such contemporaneous mechanism; in accordance with this, as discussed in Section 5.2 on Page 25, the empirical impulse response of EBP to a positive shock is significantly larger than the corresponding response to a negative shock.[8]

[8] A basic litmus test for the ability of the second step to truly capture the effect of the squared value of the true shock, as opposed to just erroneously pick up a potentially non-zero skewness of the true shock, is that the EBP response asymmetries from an estimation procedure that includes and excludes the second step

Operationally, I estimate Equation (10) for $i = 1, 2, ..., 60$, calibrating the true parameters in Equation (13) from the estimates of Equation (10) as follows: $\gamma = \hat{\gamma}_1$, $\alpha_i^1 = \hat{\alpha}_i^1$ and $\beta_{i,i}^{1,1} = \hat{\beta}_{i,i}^{1,1}$ for $i = 1, 2, ..., 60$, and $\alpha_i^1 = 0$ and $\beta_{i,i}^{1,1} = 0$ for $i > 60$.[9] Using this calibration, I generate 2000 sets of artificial samples with 543 observations each[10] from DGP (10), where v_t is assumed to follow a unit root process whose white noise shock is drawn from a standard normal distribution with variance equal to that of the residual of the estimated regression from Equation (10) at $h = 0$ and ϵ_t^1 is randomly drawn in one of two ways. The first draws ϵ_t^1 from a standard normal distribution with variance equal to that of $\hat{\epsilon}_t^1$. And the second draws ϵ_t^1 from a Pearson distribution that possesses the skewness and kurtosis (in addition to the variance) of $\hat{\epsilon}_t^1$. While both ways introduce uncertainty around ϵ_t^1, the second way does more to enhance the realism of my Monte Carlo experiment in using the observed distributional characteristics of macroeconomic shocks (in this case, a credit supply shock) and thus allowing the examination of these characteristics' implications for the identification of impulse response asymmetry.

Finally, having these artificial data series at hand, I apply to each of them an LP-based estimation for both the dichotomous specification from Regression (9) as well as the correct, second-order specification from Regression (10). I now turn to presenting the Monte Carlo evidence from doing this for both ways of drawing ϵ_t^1 mentioned above.

Simulation Results: Normally Distributed ϵ_t^1. Figures 1a and 1b show the mean estimated OLS point estimates and 97.5th and 2.5th percentile bands of impulse responses over a 5 year

are similar to one another. The reason for the validity of this litmus test is that an estimation that excludes the second step, while not able to identify the true shock series in the presence of true contemporaneous response asymmetry in EBP, is still able to identify the response asymmetry itself with this ability being robust to the distributional asymmetry of the true shock. Importantly, I have confirmed that such similarity is borne out by the data with estimated response asymmetries from including and excluding the second step of 8 and 7 basis points, respectively. This indicates that the second estimation step is likely to a good job of purging the residual from the first step and getting at the true shock as opposed to merely picking up a potentially non-zero skewness of the true shock. (The additional 1 basis point response difference estimated from including the second step can be viewed as a slight upward bias resulting from likely positive skewness of the true shock.)

[9] Assuming zero values for the first- and second-order coefficients from the 61st horizon onwards appears to be innocuous given that credit supply shocks' effects become insignificant after roughly 40 months and that, in accordance with this empirical result, theory implies impermanent effects of credit supply shocks on the real economy.

[10] This sample length is equivalent to the size of the monthly empirical sample (1974:M1-2019:M3) used in the empirical analysis of the effects of credit supply shocks conducted in the next section.

horizon from estimating Regressions (9) and (10), respectively, along with the corresponding true responses from the true DGP. Also shown are the response asymmetry estimates and true sizes, which are defined as the difference between the positive shock's effects and the negative shock's effect.

The mean estimated impulse responses are averages over Monte Carlo simulations with ϵ_t^1 drawn from a standard normal distribution as explained above on Page 16. I standardize each drawn shock series by dividing it by its standard deviation so that the shown impulse responses are with respect to one standard deviation positive/negative shock. For the estimation of the dichotomous specification (Regression (9)), I rescale the negative shock realization series by multiplying it by the ratio of the average negative realization to the average positive realization; this serves to ensure that results are not driven by size differences between positive and negative shock realizations by cancelling any size-driven effects of the two shocks. While for the dichotomous specification the impulse responses at horizon h to the positive and negative shocks are simply the respective estimated coefficients on these variables from Regression (9) (i.e., $\hat{b}_h^+$ and $\hat{b}_h^-$),[11] the responses at horizon h for the second-order specification are constructed as $\hat{\alpha}_h^1 + \hat{\beta}_{h,h}^{1,1}$ for the positive shock and as $\hat{\alpha}_h^1 - \hat{\beta}_{h,h}^{1,1}$ for the negative shock.

The results from Figure 1a indicate a meaningful bias of roughly 0.5%, or more than 100% as much as the true asymmetry, resulting from erroneously estimating Regression (9). This bias stems from an overestimation of the response to a positive shock and an underestimation of the response to a negative shock, which in turn lead to the significant overestimation of response asymmetry.

In contrast, it is apparent from Figure 1b that correctly estimating the second-order specification (Regression (10)) results in the mean estimated impulse responses being essentially identical to their true counterparts (effectively indistinguishable from one another in the figure), with the response asymmetry accordingly also estimated with no bias.

Simulation Results: Non-Normally Distributed ϵ_t^1. Figures 2a and 2b correspond to Figures 1a and 1b only that they are based on drawing ϵ_t^1 from a Pearson distribution as explained above on Page 16. As expected (see related discussion on Page 14), it is clear from Figure 2a that

[11] Notably, if there were no asymmetry, then $\hat{b}_h^+ = \hat{b}_h^-$.

the negative skewness and excessive kurtosis of the drawn shock produces an even larger bias from estimation of Regression (9) relative to the case of drawing from a normal distribution, with the underestimation of the negative shock's effects exceeding the overestimation of the positive shock's effects[12] and the response asymmetry bias amounting to nearly 1%, or about 200% as much as the true asymmetry.

In contrast, Figure 2b makes it clear that the way of drawing ϵ_t^1 bears no noticeable difference for the estimation performance for Regression (10) as the unbiasedness of the estimates continues to prevail also when the shock is drawn from the more realistic, non-normal empirical distribution of the credit supply shock from the data.

4 Empirical Evidence

The previous section has shown that estimating a second-order specification significantly outperforms estimating a dichotomous specification that divides the shock of interest into positive and negative realizations. I now turn to providing empirical evidence on the actual differences arising from using these two estimation approaches in the data for credit supply and monetary policy shocks, two macroeconomic shocks whose potential nonlinear effects have been the subject of increased attention recently. After briefly describing the data used in this section, I first present the differences for these two shocks' effects in terms of the response of industrial production. Then, focusing only on the second-order specification estimation, I proceed with trying to uncover the sign-dependent nature of the impulse responses to these shocks by examining the responses of various other macroeconomic variables.

4.1 Data

Outcome Variables. The central outcome variable I use is the log of the seasonally adjusted industrial production index, available in monthly frequency and taken from FRED. Additional variables I use to investigate the mechanism underlying the sign-dependent nature of industrial

[12]Note that this statement applies to the bias in relative terms, i.e., the difference between the estimated and true effects divided by the true effect, in line with the analytical result on the relation between skewness and bias asymmetry from Page 14 which was also stated in similar relative terms.

production's impulse responses are as follows. The first is the effective federal funds rate, which is available in monthly frequency from FRED for and is utilized to examine the potential relevance of a monetary policy based mechanism. The second is the average hourly earnings of production and nonsupervisory employees in the private sector, available in monthly frequency from FRED and meant to capture the potential amplifying role of downward wage rigidity in the transmission of adverse shocks.

The third and fourth additional variables are meant to capture the potential role of financial frictions in driving industrial production's sign-dependent response: the credit spread variable from Gilchrist and Zakrajek (2012), which is available in monthly frequency from Favara et al. (2016);[13] and the Chicago Fed non-financial leverage subindex, which is a subindex of the high frequency (weekly frequency) Chicago Fed National Financial Conditions Index (NFCI) with monthly values for this variable being obtained by averaging over the weekly observations and is available in standardized form (zero mean and unit variance) from FRED. The latter leverage measure can serve as a high frequency proxy for the level of leverage in the non-financial sector and can thus inform us about the role of the ultimate lending granted to the non-financial sector in driving the impulse response sign-dependency for industrial production.[14]

The sample coverage of the above-mentioned five outcome variables is dictated by that of the two macroeconomic shocks considered in my empirical analysis (and which I discuss next below) as well as by the credit spread's own data limitation, resulting in the following effective sample coverage: industrial production 1969:M1-2019:M3; federal funds rate 1969:M1-2019:M3; nominal hourly wage 1969:M1-2019:M3; credit spread 1973:M1-2019:M3; and non-financial leverage 1969:M1-2019:M3.

[13]The permanent link for this updated excess bond premium series is https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv.

[14]As explained in Brave et al. (2012), the NFCI is a weighted average of 100 financial indicators where the weight given to each reflects the indicators ability to explain the total variation among them. The non-financial leverage subindex is constructed as a combination of two indicators, the quarterly growth rate of the ratio of nonfinancial business debt outstanding to GDP and the quarterly growth rate of the ratio of household mortgage and consumer debt outstanding to the sum of residential investment and personal consumption expenditures on durable goods, with the latter receiving 1.3 times the weight of the former in accordance with the weighting from the systemic decomposition of the NFCI; this makes this variable a suitable high frequency proxy for the level of leverage in the non-financial sector. Brave et al. (2012) show that this non-financial leverage variable is a consistent leading indicator of financial stress and economic downturns in the U.S., generally rising during expansions and falling during recessions.

Credit Supply Shock. I construct my credit supply shock series as the standardized residual from a regression of the monthly excess bond premium variable (EBP) from Gilchrist and Zakrajek (2012) on 12 lags of own values and squared values as well as 12 lags of the values and squared values of log-first-differences of real S&P 500 (taken from Robert Shiller's webpage[15]). To construct EBP, Gilchrist and Zakrajek (2012) use micro-level data to construct a credit spread index (this is the credit spread I use as one of my outcome variables) which they decompose into a component that captures firm-specific information on expected defaults and a residual component that they term as the excess bond premium (EBP). The most updated series of the EBP variable is available from Favara et al. (2016).[16] It is in monthly frequency and covers the sample period 1973:M1-2019:M3, which results in the actual credit supply shock series covering 1974:M1-2019:M3 (owing to the 12 lags in the EBP regression mentioned above that underlies the construction of the shock series).

EBP can be interpreted as quantifying the way by which investors price default risk, i.e., their appetite for risk as far as their lending is concerned. As such, EBP's residual from a suitable past-information-based regression is a reasonable proxy for credit supply shocks. While my identification assumes that the credit supply shock is the only shock that moves EBP on impact (for details of the identification procedure, see Page 3), I use past values of stock prices to extract this shock so as to ensure that I am not mistakenly picking up various news shocks that may be driving future movements in EBP. My use of squared values of lagged EBP and stock prices stems from my desire to be as internally consistent as possible with the general nonlinear framework considered in this paper.[17] Lastly, since EBP could be contemporaneously driven by squared values of credit supply shocks, the addition of the second step of my identification procedure of regressing the residual from the first step on its squared value alleviates the concern that my identified shock series is contaminated by squared values of the credit supply shock series.

[15] http://www.econ.yale.edu/ shiller/data.htm.

[16] The permanent link for this updated excess bond premium series is https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv, the same link for which the credit spread variable used as one of my outcome variables is available at.

[17] Nevertheless, using a linear regression by removing the squared lagged terms of EBP and stock prices results in a largely similar credit supply shock series that has a correlation of 0.94 with the one from the nonlinear regression.

Monetary Policy Shock. For the monetary policy shock series, I use a monthly series running from 1969:M1-2007:M12 that is based on the methodology of Romer and Romer (2004), who suggested extracting monetary policy shocks as the residuals from regressing the federal funds target rate on FOMC members' Greenbook forecasts of output, unemployment, and inflation. Such a series, in being purged of the information content encapsulated in FOMC members' forecasts, can go a long way toward overcoming the problem of superior Federal Reserve information relative to private sector information (Romer and Romer (2000)) and thus serve as a good proxy for monetary policy shocks. The updated series I use is constructed by Wieland and Yang (2016) and is taken from the dataset used in Ramey (2016), available on Valerie Ramey's webpage.[18]

4.2 Results from the Two Estimation Approaches

In this section I present results from estimating Specifications (9) and (10) for the credit supply shock and the monetary policy shock, where the outcome variable is the log of industrial production. These results shall inform us about the actual bias in estimating sign-dependency from using a dichotomous specification instead of a second-order specification. And, importantly, the second-order specification based results can facilitate our understanding of the actual sign-dependent nature of impulse responses to credit supply and monetary policy shocks.

Sign-Dependent Impulse Responses to Credit Supply Shocks. Figures 3a and 3b depict estimated impulse responses to positive and negative credit supply shocks along with their 97.5th and 2.5th percentile bands at all horizons up to the 5 year one for Specifications (9) and (10), respectively. Also shown are the response asymmetry estimates along with their 97.5th and 2.5th percentile bands, with the response asymmetry defined as the difference between the positive shock's effects and the negative shock's effect. Inference is based on Newey-West robust standard errors that allow arbitrary correlations of the error term across time. (For details on how the credit supply shock was identified, see Page 15.)

I standardize the credit supply shock series by dividing it by its standard deviation so that the shown impulse responses are with respect to one standard deviation positive/negative shock. For

[18] https://econweb.ucsd.edu/ vramey/research.html#data.

the dichotomous specification estimation (Regression (9)), I rescale the negative shock realization series by multiplying it by the ratio of the average positive realization to the average negative realization; while this serves to ensure that results are not driven by size differences between positive and negative shock realizations, it has no significant bearing on the shown responses given that the average realizations for the positive and negative credit supply shock series turn out to be roughly similar.[19]

While for the dichotomous specification the impulse responses at horizon h to the positive and negative shocks are simply the respective estimated coefficients on these variables from Regression (9) (i.e., $\hat{b}_h^+$ and $\hat{b}_h^-$), the responses at horizon h for the second-order specification (Regression (10)) are constructed as $\hat{\alpha}_h^1 + \hat{\beta}_{h,h}^{1,1}$ for the positive shock and as $\hat{\alpha}_h^1 - \hat{\beta}_{h,h}^{1,1}$ for the negative shock.[20]

The results from Figures 3a and 3b clearly indicate large differences between estimated response asymmetries from Specifications (9) and (10), with the former (dichotomous specification) producing a peak response asymmetry of -2.8% after one year compared to a much more modest asymmetry of -0.5% at the corresponding horizon from the second-order specification. The much larger response asymmetry from the dichotomous specification is driven by large differences in both the positive shock's effect as well as the negative shock's effect, with the latter being moderately more dominant in accounting for roughly 59% of the difference between the one-year horizon response asymmetries across the two estimation approaches.

Notably, the negative shock's effect is actually significantly positive for the first year and is never negative for the dichotomous specification, while being always negative for the second-order specification and significantly so from the 5th to the 37th horizon. I.e., the dichotomous specification indicates that favorable credit supply shocks actually significantly lower industrial production. E.g., after one year, this specification indicates that industrial production falls by 0.6% following a one standard deviation negative shock as would be implied by simply multiplying

[19]Negative shocks are on average 8% larger than positive shocks. The difference is even smaller for monetary policy shocks with the average positive monetary shock realization being 5% larger than the negative one.

[20]Notably, there is no need to multiply by -1 either the positive shock's effect or the negative shock's effect in Regression (9) for comparison purposes because the estimated responses already reflect effects that go in the same direction in the absence of asymmetry. To see this, note that because they are multiplied by oppositely signed realizations, it must be that $\hat{b}_h^+ = \hat{b}_h^-$ in the presence of full symmetry.

the response to the negative shock from 3a by a negative one standard deviation shock. Mirroring these results are the insignificant responses of EBP to favorable credit supply shocks (not shown here) at effectively all horizons, with point estimates even indicating a rise in EBP (albeit insignificant) at the 2nd to 14th horizons in response to these shocks after a negligible impact EBP decline of 4 basis points compared to a corresponding 39 basis point rise following an adverse shock. This puzzling result further reinforces the notion that the dichotomous specification is prone to lead to biased results as the second-order specification yields much more reasonable results for EBP (which will be shown in Section 5.2).

Overall, there seem to be two main takeaways from Figures 3a and 3b. First, in accordance with the Monte Carlo evidence of the previous section, there appears to be very significant overestimation of the response asymmetry with respect to credit supply shocks when erroneously using the dichotomous specification from Regression (9). Second, correctly using the second-order specification still generates interesting and significant results regarding response asymmetry, with the estimated response asymmetry from this specification being significant from the 2nd to 20th horizon.

Sign-Dependent Impulse Responses to Monetary Policy Shocks. Figures 4a and 4b correspond to 3a and 3b, respectively, only that now the credit supply shock variable is replaced by the extended Romer and Romer (2004) monetary policy shock series (spanning 1969:M1-2007:M12) constructed by Wieland and Yang (2016). Similarly to the results for the credit supply shock, the results from Figures 4a and 4b also indicate large differences between estimated response asymmetries from Specifications (9) and (10), with the former (dichotomous specification) producing a peak response asymmetry of -2.9% after two years compared to a much more modest asymmetry of -0.4% at the corresponding horizon from the second-order specification. The much larger response asymmetry from the dichotomous specification is driven by large differences in both the positive shock's effect as well as the negative shock's effect, with the latter being more dominant in accounting for roughly 66% of the difference between the two-year horizon response asymmetries across the two estimation approaches.

Also in similar vein to the results for the credit supply shock, the negative monetary policy

shock's effect is actually significantly positive for the first 8 months and is never negative for the dichotomous specification, while never being significantly positive for the second-order specification and being significantly negative for this specification from the 15th horizon to the 33rd horizon. In other words, in contrast to basic theory and conventional wisdom, the dichotomous specification indicates that a negative (expansionary) monetary policy shock realization actually significantly lowers industrial production in the first 8 months that follow it.

Note that the scaling of the responses for Figure 4a according to the ratio of the mean negative realization to the mean positive realization still resulted in a significant impact response difference for the federal funds rate of 27 basis points (42 for positive shocks and only 15 for negative shocks, not shown here). Nevertheless, two observations are notable in regard to this result. First, this contemporaneous response difference is not statistically significant and, in fact, the federal funds rate is never significantly more responsive to positive shocks while becoming significantly less responsive to them from the 21st to 58th horizon. Second, industrial production never rises in response to negative shocks while always falling following positive shocks. The first observation renders my choice not to further rescale the response to negative monetary shocks such that the impact response of the federal funds rate is equalized across the two shocks a reasonable one whereas the second renders it conservative as this further rescaling would only result in an underestimation of the response asymmetry.

The two main takeaways discussed above for the results for the credit supply shock also apply to the results from Figures 4a and 4b. First, there appears to be very significant overestimation of the response asymmetry with respect to monetary policy shocks when erroneously using the dichotomous specification from Regression (9). Second, correctly using the second-order specification still generates interesting and significant results regarding response asymmetry. In fact, the response asymmetry sub-figure from Figure 4b indicates that positive (contractionary) monetary policy shocks generate effects that are significantly greater for effectively all considered horizons than the corresponding effects due to negative (expansionary) monetary policy shocks.

I now turn to inspecting the mechanism underlying the results found for the response asymmetry with respect to both the credit supply shock and the monetary policy shock. To accomplish this, I look at the sign-dependent responses of various structurally informative variables estimated

from the correct second-order specification.

5 Inspecting the Mechanism Behind Impulse Response Sign-Dependency

This section examines the potential mechanisms underlying the sign-dependent nature of impulse responses to credit supply and monetary policy shocks by looking at the sign-dependent responses of relevant variables to these shocks from estimation of Regression (10). In particular, I focus on two main potentially amplifying mechanisms for adverse shocks highlighted by the DSGE literature. The first is downward nominal wage rigidity, whose potentially amplifying role in the transmission of adverse shocks has been studied both in a close economy setting (Kim and Ruge-Murcia (2009) and Aruoba et al. (2017)) and an open economy setting (Schmitt-Grohé and Uribe (2016)). The second is financial frictions intensity, whose potentially amplifying role has been studied both in settings assuming financial frictions are based on the occasionally binding collateral constraint framework (Kocherlakota et al. (2000), Mendoza (2010), and Guerrieri and Iacoviello (2017)) as well as settings using the costly state verification framework for modeling financial frictions (Guerrieri and Iacoviello (2017)).

In addition to looking at the relevant variables for the above-mentioned two mechanisms, the federal funds rate is also considered in the estimations so as to study any potential amplifying role for systematic monetary policy. For the credit supply shock, I also examine the response of the fundamental most directly linked to it, i.e., the EBP variable, so as to uncover any potential differences in the persistence or magnitude of this variable's response.

5.1 Mechanism Behind Credit Supply Shocks' Asymmetric Effects

Excess Bond Premium. Figure 5 corresponds to Figure 3a only that now logged industrial production is replaced by the excess bond premium (EBP) variable from Gilchrist and Zakrajek (2012).[21] Note that the identification procedure underlying the extraction of the credit supply

[21] In contrast to all other outcome variables, I insert EBP into the LP regressions in levels form instead of cumulative-differences form so as to accord with its clear stationarity which in turn was also the reason for my inserting it in levels in the regression underlying the identification of credit supply shocks.

shock series (see Page 15) accounts for the possible effect of squared values of credit supply shocks on EBP. Therefore, the estimated impact response of EBP need not necessarily be the same for positive and negative shocks and can be freely estimated from the data. Since the second step of the credit supply shock identification procedure pointed to the existence of such an effect (in positive direction), it is not surprising that the impact response of EBP is significantly larger for positive shocks than for negative shocks (standing at 26 and 18 basis points, respectively), from which we are informed that there appears to be a meaningful contemporaneous sign-dependent mechanism underlying the relation between credit supply shocks and their associated fundamental (i.e., EBP). In other words, adverse initial shocks to credit markets' sentiment produce greater ultimate falls in sentiment relative to the corresponding ultimate rise in sentiment induced by favorable shocks.

Notwithstanding the aforementioned significant contemporaneous response difference, positive shocks' effects are significantly stronger than those of negative shocks for only 9 months and actually negative shocks' effects begin to be stronger than those of positive shocks from the 19th horizon onwards, with this stronger effect being marginally significant for several horizons and highly significant for two horizons (56th and 57th horizons). That is, EBP seems to be more sensitive to positive shocks mainly for the short-term while negative shocks' effects appear to be more persistent with more long-lasting effects. Hence, taking into account the entire dynamics of the sign-dependent behavior of EBP, it is not clear which effects win out: the sharper and shorter-lasting positive shocks' effects or the deeper and longer-lasting ones of negative shocks. E.g., simply averaging the responses over the 60 considered horizons results in very similar average effects of positive and negative shocks of 3 and 2 basis points, respectively; and averaging over the more reasonable business cycle frequency of 3 years results in average effects of 7 and 5 basis points, respectively. This issue is crucial for the subsequent analysis as it emphasizes that any persistent asymmetry found in other variables' responses can not be merely interpreted as arising from EBP response asymmetry. I shall return to this issue in Section 6 and investigate the validity of the latter statement from a structural perspective.

I now turn to examine the potentially asymmetric behavior of monetary policy in order to shed light on how the FED deals with the asymmetric effects of credit supply shocks on the economy.

Federal Funds Rate. Figure 6 corresponds to Figure 3b only that now logged industrial production is replaced by the effective federal funds rate. Monetary policy appears to be significantly more responsive to positive credit supply shocks than to negative ones for the first year following the shock with the peak difference reaching 14 basis points after 8 months. This asymmetric behavior of monetary policy is consistent with the significantly stronger effect on the real economy of positive credit supply shocks, which in turn induce the FED to a produce larger policy response in its attempt to alleviate the bigger response of economic activity to these shocks.

The results just shown for the federal funds rate are consistent with a stronger response of industrial production to positive credit supply shocks in documenting a stronger monetary policy response to these shocks, but they do not serve as a causal explanation for the former stronger response. In other words, there must be some amplifying mechanism that enhances the asymmetric effects of contractionary credit supply shocks in the direction observed in the data. I now turn to examine whether downward wage rigidify and/or financial frictions constitute such mechanisms.

Nominal Hourly Wage. Figure 7 corresponds to Figure 3b only that now logged industrial production is replaced by the logged average hourly earnings of production and nonsupervisory Employees in the private sector. While point estimate wise both positive and negative shocks' effects seem to make economic sense in terms of wages ultimately going down in response to positive shocks and up in response to negative shocks (as implied by multiplying the response to the negative shock shown in the figure by -1), responses to both shocks are not statistically significant and thus indicate rather strong wage rigidify both downwardly and upwardly.

Importantly, the difference between the positive and negative shocks' effects are insignificant, which is at odds with a meaningful mechanism based on asymmetric nominal wage rigidity. In fact, wages actually respond more to adverse credit supply shocks than to favorable ones, going against the notion of stronger downward rigidity than upward rigidity. But, all in all, the insignificance of the results does not allow making inference in any direction, including the economically more reasonable direction of stronger downward wage rigidity.

Credit Spread. Figure 8a corresponds to Figure 3b only that now logged industrial production is replaced by the credit spread from Gilchrist and Zakrajek (2012), which is the first of two variables I look at (the second being non-financial leverage) to ascertain the relevance of financial frictions in driving the asymmetric response of industrial production. It is clear from Figure 8a that credit conditions deteriorate significantly more initially in response to positive credit supply shocks than they improve following negative ones, as the credit spread response asymmetry is significantly positive through the first 5 months. We also see from Figure 8a that from the 17th horizon onwards the response asymmetry becomes significantly negative indicating a much faster return to steady state following positive shocks than after negative shocks. Overall, both the initially stronger response of credit spreads to positive shocks as well as the stronger persistence of the negative shock are consistent with the sign-dependent dynamics of EBP observed from Figure 5.

The results from Figure 8a indicate that adverse credit supply shocks have a larger *initial* effect on credit markets than favorable credit supply shocks but, at the same time, that credit markets conditions bounce back much more forcefully in response to the former shocks. And this stronger recovery may be related to the fact that monetary policy's initial response is significantly stronger in the presence of adverse credit supply shocks. Overall, the initially stronger response of credit spreads to positive credit supply shocks is consistent with the stronger response of industrial production to these shocks. That said, to make this evidence more whole in terms of its alignment with a story where adverse credit supply shocks induce greater intensity of financial frictions, a suitable quantity credit market variable needs to be considered. One possible explanation for quicker return to steady state following positive shocks is a stronger deleveraging process that facilitates a decline in spreads. This is what I turn to examine next.

Non-Financial Leverage. Figure 8b corresponds to Figure 3b only that now logged industrial production is replaced by the Chicago Fed non-financial leverage index variable, which complements the credit spread variable examined above in further informing us about the importance of financial frictions in driving the empirical results of this paper. In particular, since this high frequency leverage measure is a weighted average of the growth rates of *i*) the ratio of nonfi-

nancial business debt outstanding to GDP and *ii*) the ratio of household mortgage and consumer debt outstanding to the sum of residential investment and personal consumption expenditures on durable goods, where the weighting is based on the systemic decomposition of the NFCI (Brave et al. (2012)), the magnitude and timing of the sign-dependent nature of its response can inform us about whether the observed greater response of the economy to adverse credit supply shocks is related to a greater response of lending in the economy that is amplified by intensified financial frictions.

The results from Figure 8b clearly indicate that non-financial leverage is much more responsive to positive credit supply shocks than it is to negative ones. The response asymmetry is statistically significant from the impact horizon through the 42rd horizon, troughing at 0.13 standard deviation units after 27 months.[22] That non-financial leverage immediately begins to fall significantly more in response to adverse credit supply shocks relative to its rise in response to favorable credit supply shocks, coupled with the stronger initial response of credit spreads from Figure 8a, is an indication that a financial frictions based mechanism is at work here. That is, adverse credit supply shocks seem to produce a very asymmetric response of non-financial leverage which results in a severe deleveraging process that is unmatched by its corresponding leveraging process due to favorable credit supply shocks. And this stronger delevaraging process can also viewed as a force that helps credit spreads ultimately return to steady state faster after positive shocks relative to their return to steady state following negative shocks and their associated rise in leverage.

5.2 Mechanism Behind Monetary Policy Shocks' Asymmetric Effects

Federal Funds Rate. Figure 9 corresponds to Figure 4b only that now logged industrial production is replaced by the effective federal funds rate. Monetary policy appears to be mostly symmetric in its short-term response to positive and negative shocks. The only exceptions are the impact, 9th, and 10th horizons for which the associated asymmetry estimates are significantly positive at 6, 11, and 12 basis points, respectively. That the impact rise in interest rates is somewhat stronger following a one standard deviation positive monetary shock than its corresponding de-

[22]Since the non-financial leverage index is available in standardized form (zero mean and unit variance), impulse responses are in terms of standard deviation units.

cline after a one standard deviation negative one is an indication that monetary policymakers tend to surprise markets a bit more aggressively when they raise rates than when they lower them. In other words, there seems to be a modest contemporaneous sign-dependent mechanism underlying the relation between monetary policy shocks and their associated fundamental (i.e., the federal funds rate). However, given that this contemporaneous sign-dependent mechanism is quite modest and that the federal funds rate response continues to appear largely symmetric through the 21st horizon, it is sensible to argue that the any potential response asymmetries found in the other variables I look at subsequently are unlikely to be a result of an exogenous sign-dependent mechanism underlying the relation between monetary policy shocks and their associated fundamental.

Importantly, the response asymmetry becomes significantly negative from roughly two-year mark onwards, with the negative monetary shock's much more persistent effect on the federal funds rate coming into play and translating into a significant response asymmetry that surpasses -20 basis points after 3 years. This strong asymmetry can be explained by the stronger effect of positive shocks on industrial production that in turn lead to quicker return to pre-shock interest rate levels by the monetary policymakers.

Nominal Hourly Wage. Figure 10 corresponds to Figure 4b only that now logged industrial production is replaced by the logged average hourly earnings of production and nonsupervisory Employees in the private sector. While nominal wages do not seem to move significantly in response to either shock, the point estimates are still sufficiently apart to translate to significant response asymmetry that aligns well with a downward wage rigidity based mechanism.

Specifically, the responses from Figure 10 indicate that contractionary monetary policy shocks reduce wages by a mere 0.05% after two years, which is significantly less than the corresponding increase of 0.2% in wages resulting from expansionary monetary shocks. This 0.15% difference is both statistically and economically significant, emphasizing the possible existence of a downward nominal wage rigidity based transmission channel of monetary policy shocks.

Credit Spread. Figure 11a corresponds to Figure 4b only that now logged industrial production is replaced by the credit spread from Gilchrist and Zakrajek (2012), which is (as before for the

case of credit supply shocks) the first of two variables I look at (the second being non-financial leverage) to ascertain the relevance of financial frictions in driving the asymmetric response of industrial production. Figure 8a seems to indicate that financial frictions play some role in driving the asymmetric effects of monetary policy shocks, with credit spreads rising much more in response to contractionary monetary shocks that they decline in response to expansionary ones.

In particular, from the one-year mark onwards, spreads are significantly higher following positive monetary policy shocks with the peak difference taking place after two years (standing at 4 basis points). This stronger response of credit spreads to positive monetary shocks is consistent with the stronger response of industrial production to these shocks. That said, to make this evidence more whole in terms of its alignment with a story where contractionary monetary policy shocks induce greater intensity of financial frictions, a suitable quantity credit market variable needs to be considered; this is what I turn to next.

Non-Financial Leverage. Figure 11b corresponds to Figure 4b only that now logged industrial production is replaced by the Chicago Fed non-financial leverage index variable, which complements the credit spread variable examined above in further informing us about the importance of financial frictions in driving the empirical results of this paper. In particular, since this high frequency leverage measure is a weighted average of the growth rates of *i*) the ratio of nonfinancial business debt outstanding to GDP and *ii*) the ratio of household mortgage and consumer debt outstanding to the sum of residential investment and personal consumption expenditures on durable goods, where the weighting is based on the systemic decomposition of the NFCI (Brave et al. (2012)), the magnitude and timing of the sign-dependent nature of its response can inform us about whether the observed greater response of the economy to adverse credit supply shocks is related to a greater response of lending in the economy that is amplified by intensified financial frictions.

The results from Figure 11b clearly indicate that non-financial leverage is much more responsive to positive monetary policy shocks than it is to negative ones. The response asymmetry is statistically significant from the impact horizon through the 56th horizon, peaking at 0.07 standard deviation units after three years. That non-financial leverage falls significantly more in response to

contractionary monetary shocks relative to its rise in response to expansionary ones, coupled with the stronger response of credit spreads from Figure 11a, is an indication that a financial frictions based mechanism is at work here. That is, contractionary monetary shocks seem to produce a very asymmetric response of non-financial leverage which results in a severe deleveraging process that is unmatched by its corresponding leveraging process due to expansionary monetary shocks.

6 Discussion

On Page 26 I made the argument that the results from Figure 5 regarding the EBP response to positive and negative credit supply shocks did not necessarily imply that positive shocks are more detrimental for EBP than the extent to which negative shocks are favorable for it. More specifically, I emphasized that although positive shocks generate a bigger effect on EBP for the first 9 months after the shock, this differential effects mostly reverses in the periods thereafter to the point where the average effects on EBP of positive and negative shocks over the reasonable business cycle frequency of a three year horizon are quite similar at 7 and 5 basis points, respectively.[23]

Notably, simply altering the standard deviation of the negative shock so as to eliminate EBP's impact response asymmetry is misguided for two reasons. First, such rescaling would introduce size-dependence into the estimation thus not allowing for the isolation of sign-dependent effects facilitated by this paper's choice of looking at one standard deviation realizations for both positive and negative shocks (also see related discussion in Footnote 2.1). Second, such rescaling ignores the entire dynamics of EBP's response asymmetry by considering only a very limited portion of it and thus likely leads to a bias in the estimated impulse response sign-dependency.

To illustrate why this issue of the overall direction of asymmetry in the EBP response is especially important for the structural interpretation of this paper's results on credit supply shocks, consider two opposing arguments potentially arising from the results from Figure 5. The first is that the significantly stronger impact response of EBP to positive shocks that lasts also throughout the first 9 months suggests that the results of this paper on credit supply shocks are not

[23] As already discussed on Page 29, this issue of asymmetry direction in the fundamental's response to its corresponding shock is not a concern for the case of monetary policy shocks as these shocks appear to induce largely symmetric effects on the federal funds rate.

driven by endogenous sign-dependency related to financial frictions but rather by exogenous sign-dependency related to the sign-dependent nature of the stochastic process underlying EBP. The second (opposing) argument is that one need not look at just the impact horizon or even the first-year horizon when trying to ascertain the overall asymmetry in the EBP response; rather, the whole dynamics of EBP need to be considered by accounting for the differentially persistent response of EBP to negative shocks. In what follows, I use a simple capital market equilibrium model that builds on the costly state verification (CSV) problem between lenders and borrowers from Townsend (1979) (and as later used in Bernanke et al. (1999) (BGG)), proxying for credit supply shocks in this setting with 'risk shocks' (Christiano et al. (2014)), to demonstrate that the second argument stands on much firmer ground than the first; for expositional purposes, I defer the presentation of the model to Appendix A. Specifically, I conduct two experiments: first, an experiment that computes sign-dependent responses to risk shocks when accounting for the entire dynamics of EBP's response asymmetry and, second, an experiment that computes these responses when shutting down this asymmetry altogether.

First Experiment: Accounting for Asymmetry in EBP Response. In the first experiment I assume a stochastic process for borrower riskiness (defined as the variance of the borrower's idiosyncratic productivity) that is consistent with the one implied by the impulse responses from Figure 5. Specifically, I compute quarterly averages of the monthly effects from this Figure (so as to conform to the quarterly frequency of my model) and let the risk variable (borrower riskiness) be driven by a second-order moving average process containing the coefficients implied by the responses from Figure 5. I.e., I use the following process for risk (σ_t):

$$\sigma_t = \bar{\sigma} + \alpha_1 \eta_t + \beta_1 \eta_t^2 + \alpha_2 \eta_{t-1} + \beta_2 \eta_{t-1}^2 + ... + \alpha_{20} \eta_{t-1} + \beta_{20} \eta_{t-20}^2, \tag{14}$$

where $\bar{\sigma}$ is the steady state value of risk; η_t is a white noise shock with unit standard deviation referred to as 'risk shock' (Christiano et al. (2014)); and the α's and β's are taken from the quarterly averages of the estimated effects from Figure 5, normalized such that absent asymmetry risk would rise (decline) by 0.05 on impact in response to a positive (negative) shock.

Second Experiment: Shutting Down the Asymmetry. In the second experiment I assign zeroes to $\beta_1, \beta_2, ..., \beta_{20}$ on the premise that such an assignment would allow me to ascertain the true direction of EBP response asymmetry in terms of how if affects the asymmetry in other variables' responses. In other words, I impose on σ to respond symmetrically to positive and negative shocks for all considered horizons, which in turn enables me to examine how this shutting down of the asymmetry alters the model's response asymmetry.

Results from the Two Experiments. Figures 12a and 12b present the sign-dependent impulse responses from the experiment where data-consistent exogenous sign-dependence is accounted for (the first experiment) and from the experiment where it is shut down (the second experiment), respectively. Clearly, accounting for this sign-dependence has considerable implications for the asymmetry in the model's responses: when accounting for the data-consistent exogenous sign-dependence relative to when this sign-dependence is shut down, all endogenous variables respond much more strongly to the negative shock from the horizon at which this shock begins to have a stronger effect on risk (the 4th horizon), with the most notable difference relating to investment. This variable, which represents the central real variable in this model, only responds more strongly to the positive shock than to the negative shock for the first three horizons when the data-consistent exogenous sign-dependence is accounted for, with the negative shock's effects outweighing those of the positive shock from the 5th to 14th horizon, while responding more strongly for three straight years when this sign-dependence is shut down.[24,25] Moreover, invest-

[24]The basic intuition for why investment response asymmetry obtains in this model even in the absence of exogenous sign-dependence is that, for given leverage, higher risk causes the external finance premium (EFP) to increase by more (and thus raises borrowing costs by more) than the decline in EFP caused by a corresponding decrease in risk. This asymmetry result is based on the convexity of lenders' expected monitoring costs (in case of default) in risk which in turn implies a greater effect of positive risk shocks on EFP and investment than the corresponding effect of negative shocks. These results are formalized in Appendix A.4.

[25]Granted, my empirical analysis did not look at investment given the monthly frequency nature of my analysis. However, the purpose of the structural exercise of this section is not to build a quantitative theoretical analysis that speaks to the empirical analysis in terms of the specific variables each analysis considers. Nor is it aimed at matching the empirical responses of the variables that do overlap in the two analyses. (E.g., although lowering the 'death rate' of entrepreneurs goes a long way toward better matching the empirical and theoretical leverage responses, note that for the baseline calibration leverage exhibits neither the absolute nor the differential deleveraging process observed in the data.) Rather, while very stylized and simple, the structural framework I use aims to serve as a lens through which we can ascertain

ment responses to the negative shock are quite similar for both experiments in the periods leading up to the reversal in response asymmetry direction.

In other words, from a structural standpoint, the asymmetric behavior of EBP in the data serves as an exogenous amplification mechanism for the effects of negative shocks relative to positive shocks' effects, leaving the former mostly unchanged for the first three quarters but significantly amplifying them thereafter. This suggests that the empirical results of this paper on credit supply shocks need not be interpreted as arising from an exogenous sign-dependent mechanism underlying the EBP process. Rather, if anything, such exogenous mechanism is expected to go in the other direction of pushing negative shocks' effects to be stronger than positive shocks' effects so that there are likely to be additional (endogenous) sign-dependent mechanisms pushing this paper's results on credit supply shocks in the other direction. My analysis highlighted financial frictions as such endogenous sign-dependent mechanism and the results of this section further validate the relevance of this interpretation of my results.

7 Conclusion

This paper has provided evidence which suggests that wrongly using a dichotomous specification (i.e., including positive and negative shock realizations as regressors) as opposed to a correct second-order one can have important implications for the proper quantification of the economy's response asymmetries. To obtain this evidence, I first established the analytical bias from estimating the dichotomous specification and then resorted to applying the two opposing estimation approaches to both Monte Carlo based artificial data as well as actual data. The Monte Carlo based evidence indicates that meaningful bias can stem from erroneously using the dichotomous specification and the empirical evidence confirms this bias in showing major differences between the results from these two estimation approaches.

Importantly, after establishing the suitability of the second-order specification's estimation for properly quantifying impulse response sign-dependency, I proceeded with an investigation into the structural mechanisms underlying the results found for contractionary credit supply and mon-

the direction with which the sign-dependent response of EBP in the data amplifies the asymmetrical nature of positive and negative risk shocks' effects.

etary poicy shocks having stronger effects on industrial production. Toward this end, I examined the sign-dependent responses of various structurally informative variables such as the federal funds rate, nominal hourly wage, credit spreads, and non-financial leverage. This examination leads to significant evidence that contractionary shocks produce stronger intensification of financial frictions than the alleviation of these frictions induced by expansionary shocks; downward nominal wage rigidity receives more limited support as an asymmetry-production mechanism, being relevant only for monetary policy shocks.

Overall, the analysis undertaken in this paper stresses the caution that need be taken when assuming a dichotomous DGP for the estimation of impulse response sign-dependency. And, notably, the findings from this paper's analysis can serve as relevant evidence for model builders in emphasizing the central role financial frictions seem to posses in producing impulse response asymmetries.

Appendix A Structural Model with Asymmetric Effects of Credit Supply Shocks

This appendix presents a stochastic dynamic capital market equilibrium model whose purpose is to ascertain the direction with which the sign-dependent response of EBP in the data amplifies the asymmetrical nature of positive and negative risk shocks' effects. This in turn could help in validating the structural interpretation of this paper's results on credit supply shocks as arising from an endogenous, financial-frictions-based sign-dependent mechanism. The model builds on the costly state verification (CSV) problem between lenders and borrowers from Townsend (1979) (and as later used in Bernanke et al. (1999) (BGG)), proxying for credit supply shocks in this setting with 'risk shocks' (Christiano et al. (2014)).

Granted, one can pursue a more ambitious, full-blown DSGE model that incorporates additional asymmetry-inducing frictions that go beyond BGG-type financial frictions. That said, this would go beyond the scope of what I intend for this structural exercise to be which is to limit the analysis to the simplest possible setting where financial-friction-induced endogenous sign-dependence obtains (consistent with the data). Hence, I opt to keep things as simple as possible while still allowing me to establish a suitable lens through which to I can analyze the direction of the asymmetrical implications of the exogenous sign-dependence found in the data.

A.1 Entrepreneurs

There is a continuum of identical, finitely-lived, and risk-neutral entrepreneurs. The i-th entrepreneur produces good $Y_{i,t}$ using the following technology:

$$Y_{i,t} = \omega_{i,t} K_{i,t}^{\alpha}, \tag{15}$$

where $\omega_{i,t}$ is a random idiosyncratic productivity shock which is assumed to be log-normally distributed $ln\omega_{i,t} \sim N(\frac{-\sigma_t^2}{2}, \sigma_t^2)$ so that $\mathbb{E}(\omega_{i,t}) = 1$; and $K_{i,t}$ is physical capital of the i-th entrepreneur.

Entrepreneurs purchase capital from capital producers in the beginning of period t at price Q_{t-1}, which they then operate in period t and resell it at the end of the period at price Q_t. The gross real rate of return on capital for the i-th entrepreneur, denoted by $R_{i,t}^k$, is the sum of the

marginal profitability of capital and the capital gain:

$$R_{i,t}^k = \frac{\alpha K_{i,t}^{\alpha-1} + (1-\delta)Q_t}{Q_{t-1}}, \tag{16}$$

where δ is the rate of capital stock depreciation.

Entrepreneurs' capital purchases are financed partly internally and partly by borrowing from risk-neutral financial intermediaries within a CSV framework, such that the assets of entrepreneurs $Q_t K_{t+1}$ at the beginning of period $t+1$ are the sum of their debt B_{t+1} and net worth N_{t+1}:

$$Q_t K_{t+1} = D_{t+1} + N_{t+1}. \tag{17}$$

The focal assumption underlying the CSV problem is that the realization of $\omega_{i,t}$ is private information of the borrower and that in order to observe it the lender has to pay a monitoring cost of $\mu\omega_{i,t}R_t^k Q_{t-1}K_t$, where $0 < \mu < 1$ is the monitoring cost parameter. The optimal debt contract between the borrower and the lender specifies that, in the case of no default, the former pays the lender ZB, where Z is the no-default contractual interest rate; that is, if $\omega_{i,t}R_t^k Q_{t-1}K_t \geq Z_t B_t$, the borrower will pay the debt and retain any residual profit. In the case of default, i.e., $\omega_{i,t}R_t^k Q_{t-1}K_t < Z_t B_t$, the lender will pay the monitoring cost and obtain $(1-\mu)\omega_{i,t}R_t^k Q_{t-1}K_t$. It is straightforward to define the default threshold value of $\omega_{i,t}$, $\bar{\omega_{i,t}}$, as $\bar{\omega_{i,t}} = \frac{Z_t B_t}{R_t^k Q_{t-1}K_t}$. As formalized below, the optimal contract will specify $\bar{\omega_{i,t}}$ and K_t as the choice variables, which is equivalent to specifying Z_t and B_t as the choice variables due to the relations $\bar{\omega_{i,t}} = \frac{Z_t B_t}{R_t^k Q_{t-1}K_t}$ and $Q_{t-1}K_t = B_t + N_t$.

I now turn to presenting the maximization problem that characterizes the optimal debt contract. Assuming that the lender operates in a perfectly competitive environment in which she earns, in expectation, the gross risk-free return R_t, the optimal contract problem that maximizes the borrower's expected profit subject to the lenders' zero-profit condition is

$$\begin{aligned} &\max_{K,\bar{\omega_{i,t}}} \int_{\bar{\omega_{i,t}}}^{\infty} \mathbb{E}_{t-1}\left[\omega R_t^k Q_{t-1}K_t - Z_t B_t\right] dF(\omega) = \mathbb{E}_{t-1}\left[1 - \Gamma(\bar{\omega_{i,t}})\right] R_t^k Q_{t-1}K_t \\ &s.t \;\; R_t(Q_{t-1}K_t - N_t) = \left[\Gamma(\bar{\omega_{i,t}}) - \mu G(\bar{\omega_{i,t}})\right] R_t^k Q_{t-1}K_t, \end{aligned} \tag{18}$$

where $F(\omega_{i,t})$ is the CDF; $\Gamma(\bar{\omega}_{i,t}) \equiv \int_0^{\bar{\omega}_{i,t}} \omega_{i,t} dF(\omega_{i,t}) + \bar{\omega}_{i,t} \int_{\bar{\omega}_{i,t}}^{\infty} dF(\omega_{i,t})$; and $G(\bar{\omega}_{i,t}) \equiv \int_0^{\bar{\omega}_{i,t}} \omega_{i,t} dF(\omega_{i,t})$. The first component of $\Gamma(\bar{\omega_{i,t}})$ (which is also equal to $G(\bar{\omega_{i,t}})$) gives the borrower's expected return

in case of a default, whereas the second one gives the expected return in case of solvency; hence, the optimization constraint dictates that the expected returns of the lenders on a risky loan net of monitoring costs, given by the RHS of the constraint, be equal to the risk-free return given by the LHS of the constraint. For future reference, as in BGG, I define the external finance premium (EFP) as $s_t \equiv \frac{\mathbb{E}_{t-1}R_t^k}{R_t}$ and Leverage as $k_t \equiv \frac{Q_{t-1}K_t}{N_t}$.

I assume that risk as measured by σ_t, the variance of entrepreneurial idiosyncratic productivity, follows the stochastic process

$$\sigma_t = \bar{\sigma} + \alpha_1\eta_t + \beta_1\eta_t^2 + \alpha_2\eta_{t-1} + \beta_2\eta_{t-1}^2 + ... + \alpha_{20}\eta_{t-1} + \beta_{20}\eta_{t-20}^2, \tag{19}$$

where $\bar{\sigma}$ is the steady state value of risk; η_t is a white noise shock with unit standard deviation referred to as 'risk shock' and given the interpretation of a credit supply shock (Christiano et al. (2014)); and the α's and β's are taken from the quarterly averages of the estimated effects from Figure 5, normalized such that absent asymmetry risk would rise (decline) by 0.05 on impact in response to a positive (negative) shock.[26]

The last piece of modelling the entrepreneurial sector is to lay out the dynamics of the net worth of entrepreneurs.[27] Toward this end, I make the standard assumption that entrepreneurs "die" with a constant exogenous probability in each period, $1 - v$, in which case they simply consume their entire net worth and are replaced within the period by new entrepreneurs.[28] This setting implies the following law of motion for aggregate entrepreneurial net worth:

$$N_{t+1} = v[1 - \Gamma(\bar{\omega}_t)]R_t^k Q_{t-1}K_t, \tag{20}$$

where K_t is aggregate capital stock in the economy and $[1 - \Gamma(\bar{\omega}_t)]R_t^k Q_{t-1}K_t$ is the aggregate profit of all entrepreneurs in period t, which also corresponds to the objective function in Problem (18).

[26] Christiano et al. (2014) estimated impulse responses to a risk shock realization of 0.07, or 26% of their estimated value of the steady state of σ_t, so my choice of a 0.05 response of σ_t in the absence of asymmetry (which is less than 18% of my BGG based calibrated value for $\bar{\sigma}$) can be viewed as a conservative one.

[27] BGG show that the chosen optimal level of $\bar{\omega}_{i,t}$ is identical across borrowers. This result is important as it facilitates aggregation of net worth in the economy.

[28] This assumption guarantees that entrepreneurs will never accumulate enough net worth so as to avoid borrowing to finance their operations.

A.2 Capital Producers

There are perfectly competitive capital producers that use a linear technology to produce capital goods which are sold at the end of period t to entrepreneurs at price Q_t. They use a fraction of final goods purchased from entrepreneurs as investment goods, I_t, which are then used in conjunction with the existing capital stock to produce new capital goods, K_{t+1}. Capital producers are also subject to the convex investment adjustment cost function of Christiano et al. (2005), resulting in the following capital accumulation equation:

$$K_{t+1} = (1-\delta)K_t - \left[1 - \Theta\left(\frac{I_t}{I_{t-1}}\right)\right] I_t, \tag{21}$$

where Θ is the adjustment cost function, with $\Theta(1) = \Theta'(1) = 0$ and $\Theta''(1) > 0$.[29] The capital producers optimization problem consists of choosing the quantity of investment to maximize the present value of their infinite stream of profits:

$$\max_{\{I_t\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \frac{1}{R_t^t} Q_t \left[1 - \Theta\left(\frac{I_t}{I_{t-1}}\right)\right] I_t - I_t. \tag{22}$$

A.3 Solution and Calibration

I solve the model by taking a second order approximation of its system of equilibrium equations about the steady state values of the variables. Using a second order approximation for solving the model is necessary for properly studying the possible asymmetric effects of risk shocks. To compute the sign-dependent responses of the variables, I produce two simulations of the model where one draws a risk shock realization of 1 and the other a -1 realization.

Table A.1 presents the calibration used for the model's parameters. The calibration for the parameters underlying the CSV problem and net worth accumulation (μ, $\bar{\sigma}$, and v) as well as the risk-free rate steady state level, capital share, and capital depreciation rate follows BGG. The convexity parameter of the investment adjustment cost function (φ) follows the estimated value from Christiano et al. (2005).

In the main text (in Section 6) I present the model economy' sign dependent responses for two cases: one that uses the shock process from Equation (19) and another that uses a modified version

[29] I assume the following investment adjustment cost function: $\Theta\left(\frac{I_t}{I_{t-1}}\right) = \frac{\varphi}{2}\left(\frac{I_t(j)}{I_{t-1}(j)} - 1\right)^2$.

of this process by assigning zeros to $\beta_1, \beta_2, ..., \beta_{20}$. I dedicate the remaining part of this appendix to elucidating why even in the absence of exogenous sign-dependence (i.e., the latter case) there is asymmetry in the model's response to positive and negative risk shocks.

A.4 EFP-Leverage Curve and Risk

The central motivation for my focusing on the CSV setting as the conceptual framework for the structural exercise from Section 6 is based on the notion that increased risk (σ) raises EFP for a given leverage more than the reduction in EFP caused by decreased risk.[30] To show this asymmetry, I proceed in two steps. First, I provide the basic intuition for the validity of this notion. Second, I formally show that this notion is correct by looking at the EFP-leverage curve for alternative risk levels. In both steps I consider only the CSV-related part of the model and analyze it in steady state, thus omitting time indices from the notation in what follows.

Basic Intuition. To provide the basic intuition underlying the asymmetric effects of risk on the EFP-leverage curve, I center my attention around the lender's expected monitoring cost, which is the focal element of the CSV problem in that its existence produces a positive EFP. In particular, I aim to show mechanically that this expected cost is convex in risk. This is obtained in a mechanical way because I will treat $\bar{\omega}$ and μ as exogenous to my computation. In the second step of this section I will solve the entire CSV problem; for now I merely want to show that the mathematical term that encapsulates expected monitoring cost is convex in risk.

Recall that this expected cost is defined as $\mu G(\bar{\omega}) \equiv \mu \int_0^{\bar{\omega}} \omega dF(\omega)$. If, for reasonable values of $\bar{\omega}$ and μ, the expected monitoring cost can be shown to be convex in risk, this would mean that higher risk entails greater expected monitoring cost for lenders than the reduction in them implied by lower risk. And this, in turn, can serve as intuition for why the EFP-leverage curve shifts upward more when risk rises than downward when risk goes down.

Figure A.1 shows the relation between expected monitoring cost and risk for the baseline $\bar{\omega} =$

[30] The nonlinear implications of risk in a CSV setting have also been highlighted recently in Harding and Wouters (2019), albeit in the context of the fact that the EFP-leverage elasticity is increasing in risk which has implications for the state-dependency of financial frictions but can not produce the kind of asymmetry focused on here.

0.48 and $\mu = 0.12$ values from BGG. This relation was obtained by forming a grid of σ that ranges between 0.23 and 0.33 with spacing of 0.001 and computing $\mu G(\bar{\omega})$ for each value in this grid. Notably, expected monitoring cost is clearly convex in risk. To see this numerically, note that rising in risk from 0.28 to 0.33 implies a rise in expected monitoring cost that is 133% greater than the rise induced by increasing risk from 0.23 to 0.28. This convexity stems from the fact that, due to the rightward skewness of the log-normal distribution, greater risk raises the expected ω conditional on being in the default range $[0, \bar{\omega}]$ more than the reduction in it induced by lower risk. While mechanical by nature in not accounting for the endogeneity of the default range, this convexity still implies that increased risk has a mechanical basis for exacerbating the agency problem between the lender and the borrower much more than the alleviation of this problem induced by decreased risk. And this consequently potentially opens the door for there being asymmetric effects of risk on EFP, as formalized by the result I turn to next.

Asymmetric Effects of Risk on EFP. I conduct the following numerical experiment. For three values of borrower's riskiness $\sigma = [0.23, 0.28, 0.33]$ (the middle value of $\sigma = 0.28$ is in line with BGG), I solve Problem (18) for a grid of s that ranges between 1.001 and 1.02 and has a spacing of 0.001, while keeping constant the monitoring cost parameter at $\mu = 0.12$ (as in BGG). The results from this experiment are shown in Figure A.2, where the solid line depicts the EFP-leverage curve for $\sigma = 0.28$ and the dashed and dotted lines correspond to $\sigma = 0.23$ and $\sigma = 0.33$, respectively. The logs of EFP and leverage appear on the y- and x-axis so that the slope of the curve can be considered the elasticity of EFP with respect to leverage.

We are now in position to state the main result of this section, i.e., that a rise in σ for a given leverage raises EFP by more than the corresponding EFP decline induced by an equivalent decrease in σ. This result is graphically illustrated by Figure A.2 in that the vertical gap between the higher risk curve and the intermediate risk curve is larger than that between the intermediate risk curve and the lower risk curve. To see this with a simple numerical example, consider the value of logged leverage which correspond to the steady state in BGG, i.e., $lnk = 0.69$. For this leverage value, logged EFP rises by 0.0066 when σ rises from 0.28 to 0.33 while only declining by 0.0044 when σ goes down to 0.23. In other words, an increase in risk shifts the EFP-leverage curve

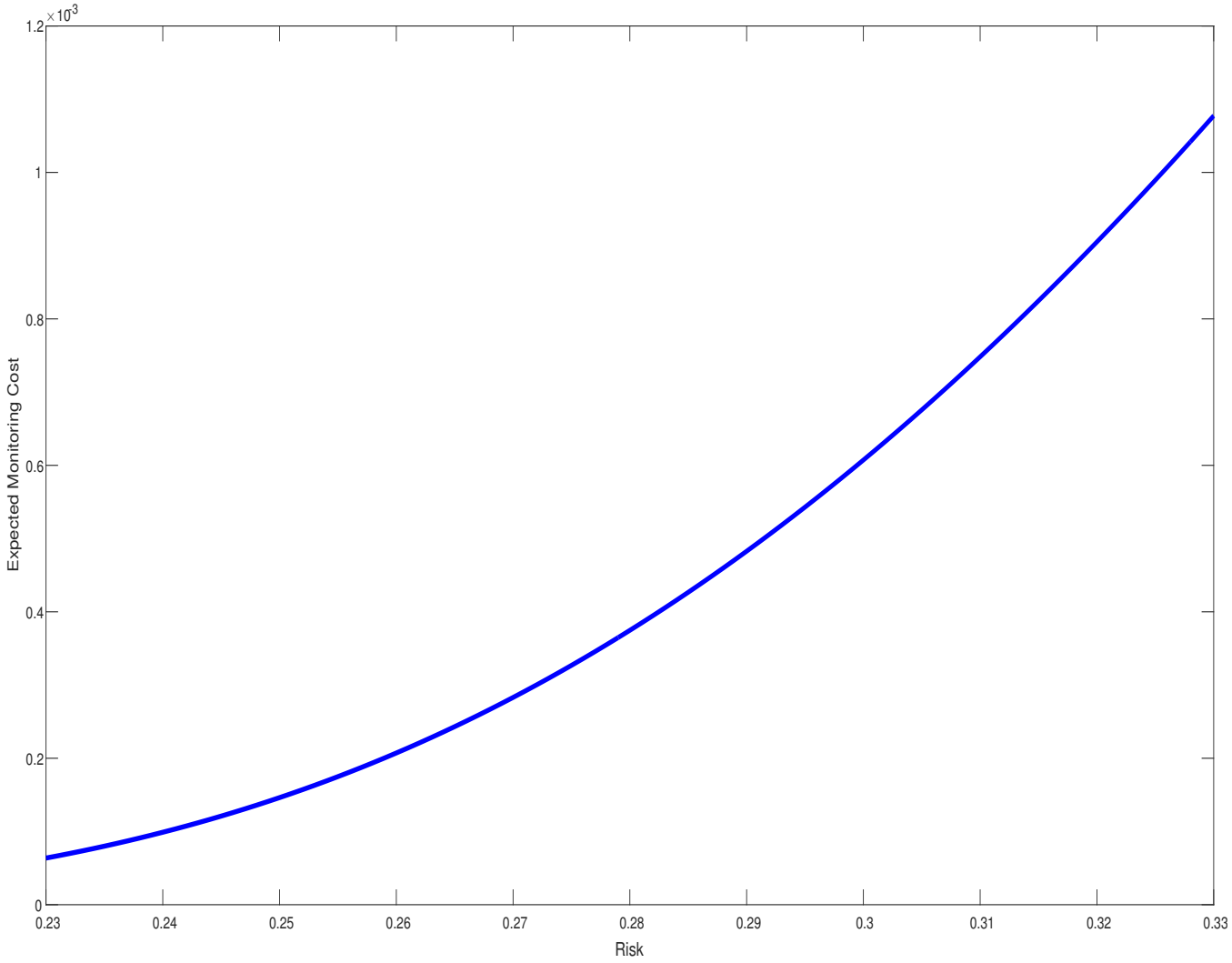
upward by more than the corresponding downward shift induced by lower riskiness. Such asymmetry, where a rise in risk increases EFP by 50% more than the corresponding decline when risk decreases, has the potential to lead to asymmetric effects of risk shocks in a stochastic dynamic environment, which is what is formally shown in Figure 12b (which is presented in Section 6).

Table A.1: **Model Parameterization**.

Parameter	Description	Value
$\bar{R}$	Steady State Gross Risk-Free Rate	1.01
α	Capital Share	0.35
ϖ	Convexity Parameter of Investment Adjustment Cost Function	2.5
δ	Depreciation Rate	0.025
υ	Entrepreneurs' Survival Rate	0.9728
μ	Monitoring Cost	0.12
$\bar{\sigma}$	Steady State S.D. of Idiosyncratic Productivity	0.28

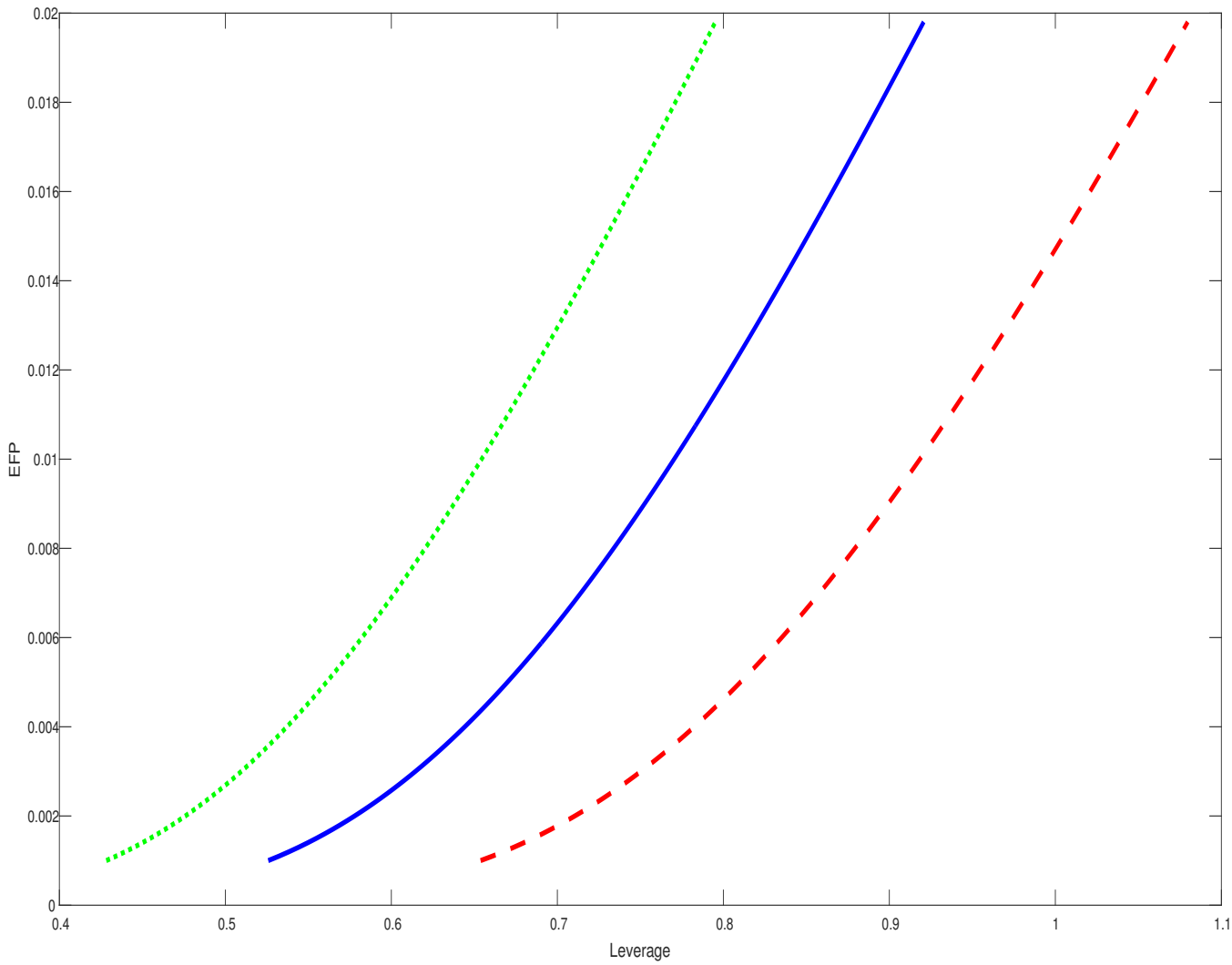
Notes: This table consists of the parameters' values used for the model from Appendix A.

Figure A.1: **Expected Monitoring Cost and Risk**.



Notes: This figure presents the relation between expected monitoring cost and risk (as defined in relation to the CSV problem described in Appendix A.1), which is obtained as follows: For the baseline values from BGG of $\bar{\omega} = 0.48$ (in steady state) and $\mu = 0.12$, I compute the expected monitoring cost for a grid of σ that ranges between 0.23 and 0.33 and has a spacing of 0.001. The solid line is the curve depicting this computation. Risk (σ) appears on the x-axis and Expected monitoring cost ($\mu G(\bar{\omega})$) is on the y-axis.

Figure A.2: **EFP-Leverage Curve and Risk**.



Notes: This figure presents the EFP-leverage curve for the CSV problem from Appendix A.1, which is obtained as follows: For three values of borrower's riskiness $\sigma = [0.23, 0.28, 0.33]$ (the middle value of $\sigma = 0.28$ is in line with BGG), I solve Problem (18) for a grid of s (i.e., EFP) that ranges between 1.001 and 1.02 and has a spacing of 0.001, while keeping constant the monitoring cost parameter at $\mu = 0.12$ (as in BGG). The solid line is the EFP-leverage curve for $\sigma = 0.28$, the dashed line corresponds to $\sigma = 0.23$, and the dotted line corresponds to $\sigma = 0.33$. Logged leverage appears on the x-axis and logged EFP is on the y-axis.

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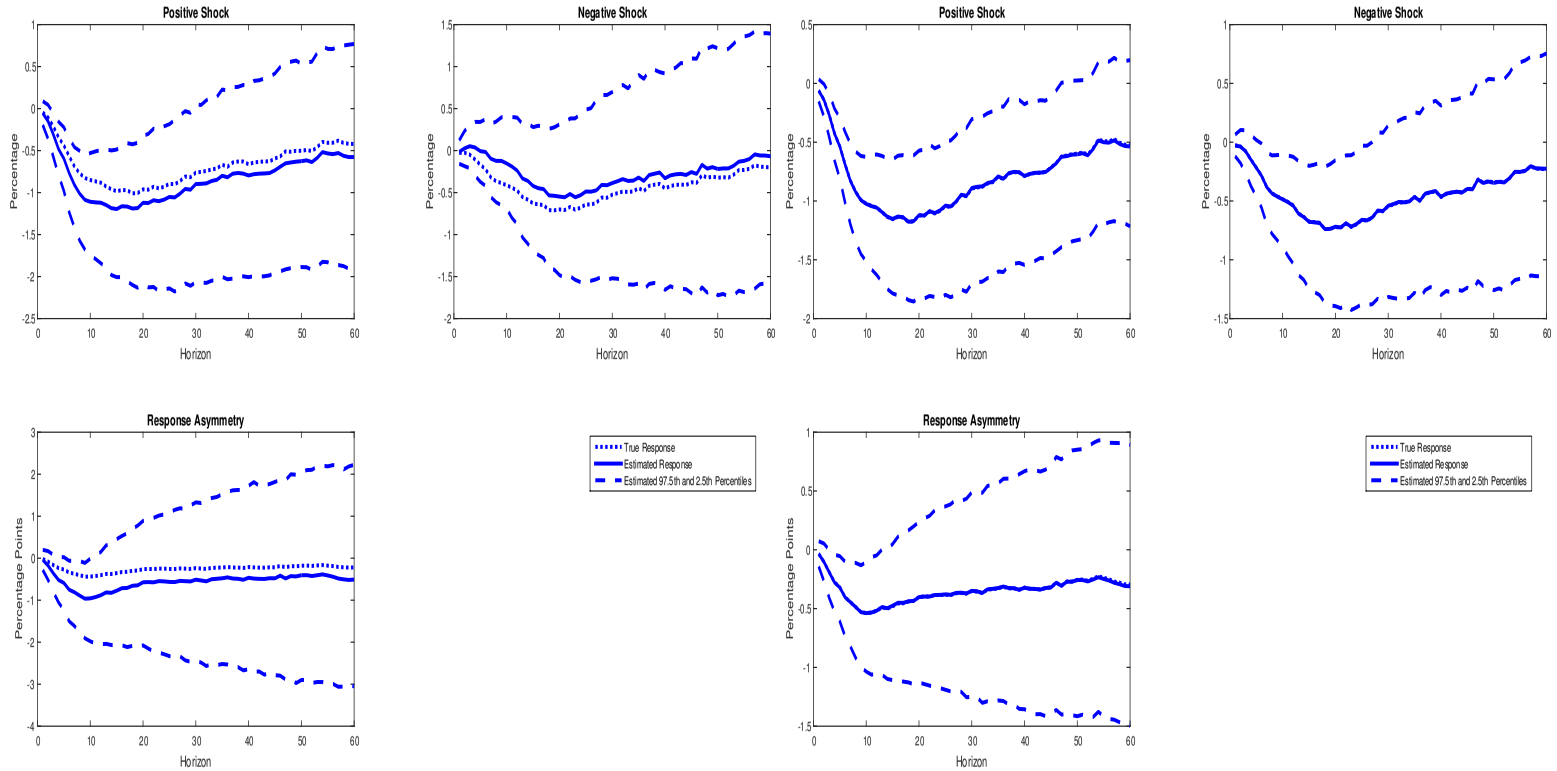
Figure 1: **Monte Carlo Evidence - Drawing Shocks from a Normal Distribution: (a) Dichotomous Specification; (b) Second-Order Specification.**

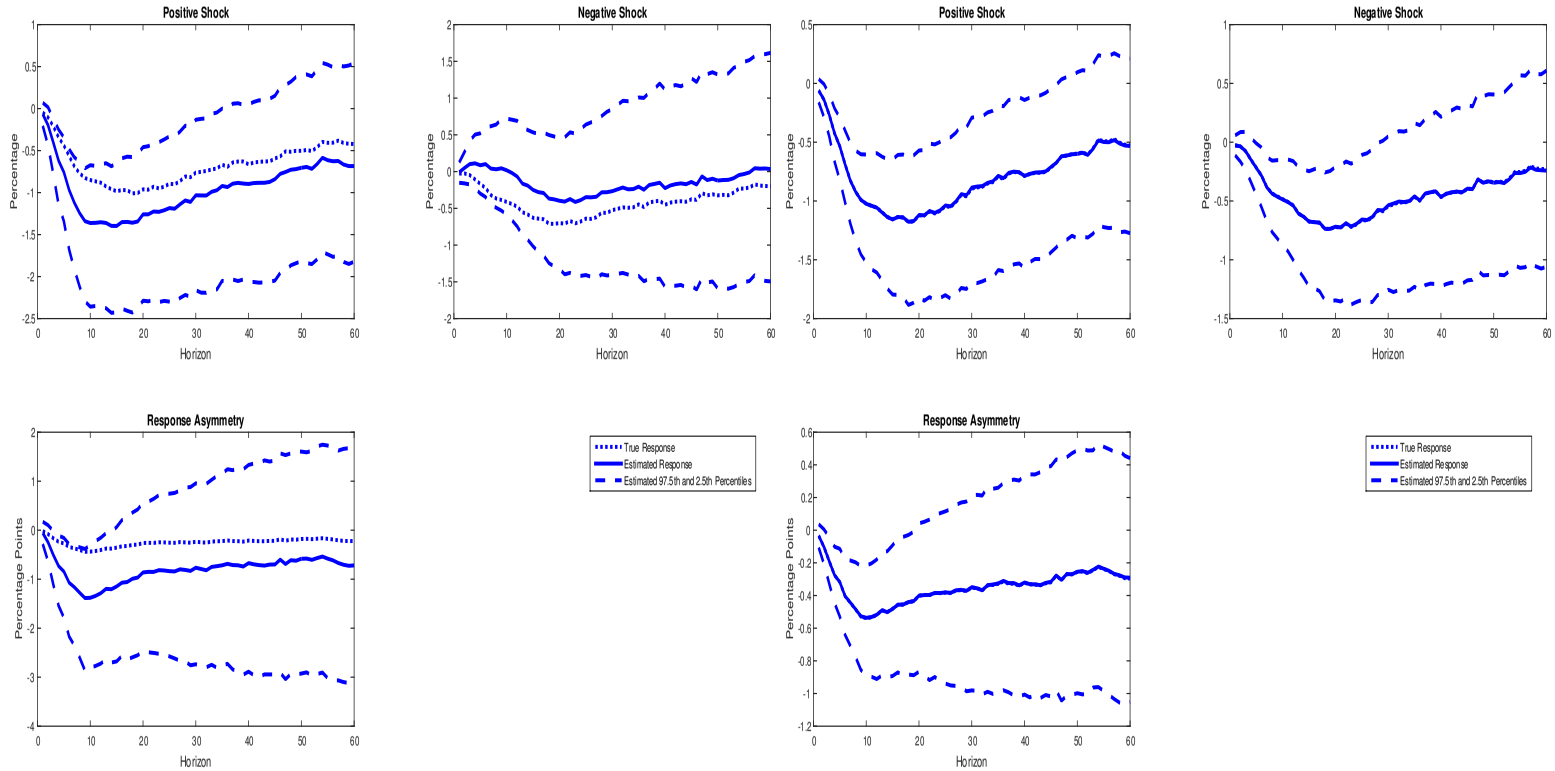


(a) The Mean and 97.5th and 2.5th Percentiles of Estimated Sign-Dependent Impulse Responses and the True Sign-Dependent Impulse Responses.

(b) The Mean and 97.5th and 2.5th Percentiles of Estimated Sign-Dependent Impulse Responses and the True Sign-Dependent Impulse Responses.

Notes: This figure presents Monte Carlo evidence on the identification of impulse response asymmetry from applying an LP-based estimation of Regressions (9) and (10) to artificial data generated from DGP (13) where ϵ_t^1 is drawn from a standard normal distribution that possesses the variance of a credit supply shock measured as the residual of a regression of EBP on 12 own lagged values and squared values as well as 12 lags of the log-first-differences of the real S&P 500 index. Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates and true sizes are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the average of estimated impulse response across monte carlo simulations from estimating Regression (9), the dashed lines are the 97.5th and 2.5th percentiles of estimated impulse response across monte carlo simulations, and the dotted line represents the true impulse responses. Panel (b): The solid line is the average of estimated impulse response across monte carlo simulations from estimating Regression (10), the dashed lines are the 97.5th and 2.5th percentiles of estimated impulse response across monte carlo simulations, and the dotted line represents the true impulse responses.

Figure 2: **Monte Carlo Evidence - Drawing Shocks from a Non-Normal Distribution: (a) Dichotomous Specification; (b) Second-Order Specification.**

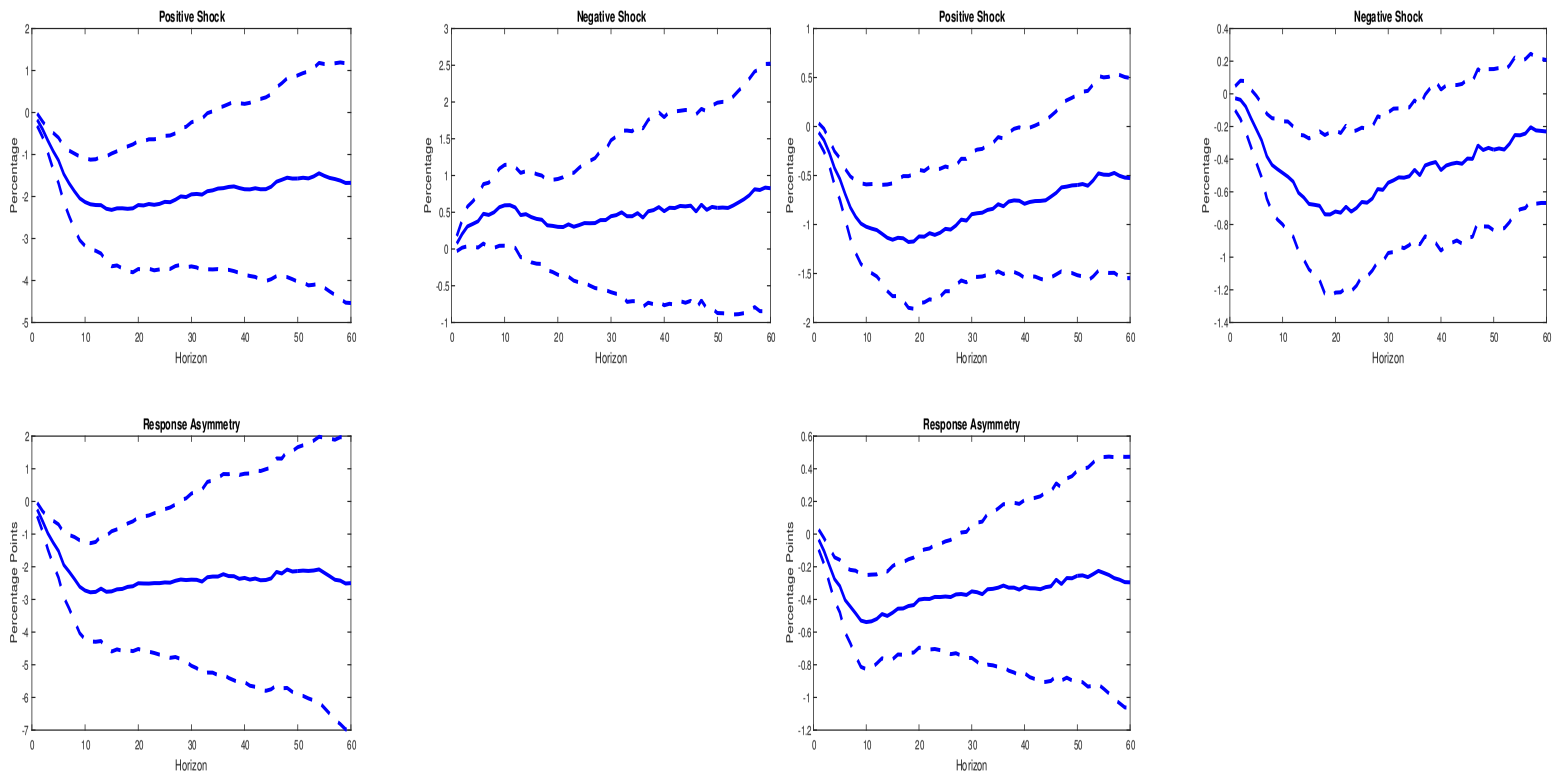


(a) The Mean and 97.5th and 2.5th Percentiles of Estimated Sign-Dependent Impulse Responses and the True Sign-Dependent Impulse Responses.

(b) The Mean and 97.5th and 2.5th Percentiles of Estimated Sign-Dependent Impulse Responses and the True Sign-Dependent Impulse Responses.

Notes: This figure presents Monte Carlo evidence on the identification of impulse response asymmetry from applying an LP-based estimation of Regressions (9) and (10) to artificial data generated from DGP (13) where ϵ_t^1 is drawn from a Pearson distribution that possesses (on top of the variance) the skewness and kurtosis of a credit supply shock measured as the residual of a regression of EBP on 12 own lagged values and squared values as well as 12 lags of the log-first-differences of the real S&P 500 index. Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates and true sizes are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the average of estimated impulse response across monte carlo simulations from estimating Regression (9), the dashed lines are the 97.5th and 2.5th percentiles of estimated impulse response across monte carlo simulations, and the dotted line represents the true impulse responses. Panel (b): The solid line is the average of estimated impulse response across monte carlo simulations from estimating Regression (10), the dashed lines are the 97.5th and 2.5th percentiles of estimated impulse response across monte carlo simulations, and the dotted line represents the true impulse responses.

Figure 3: **Sign-Dependent Impulse Responses to Credit Supply Shocks: (a) Dichotomous Specification; (b) Second-Order Specification.**

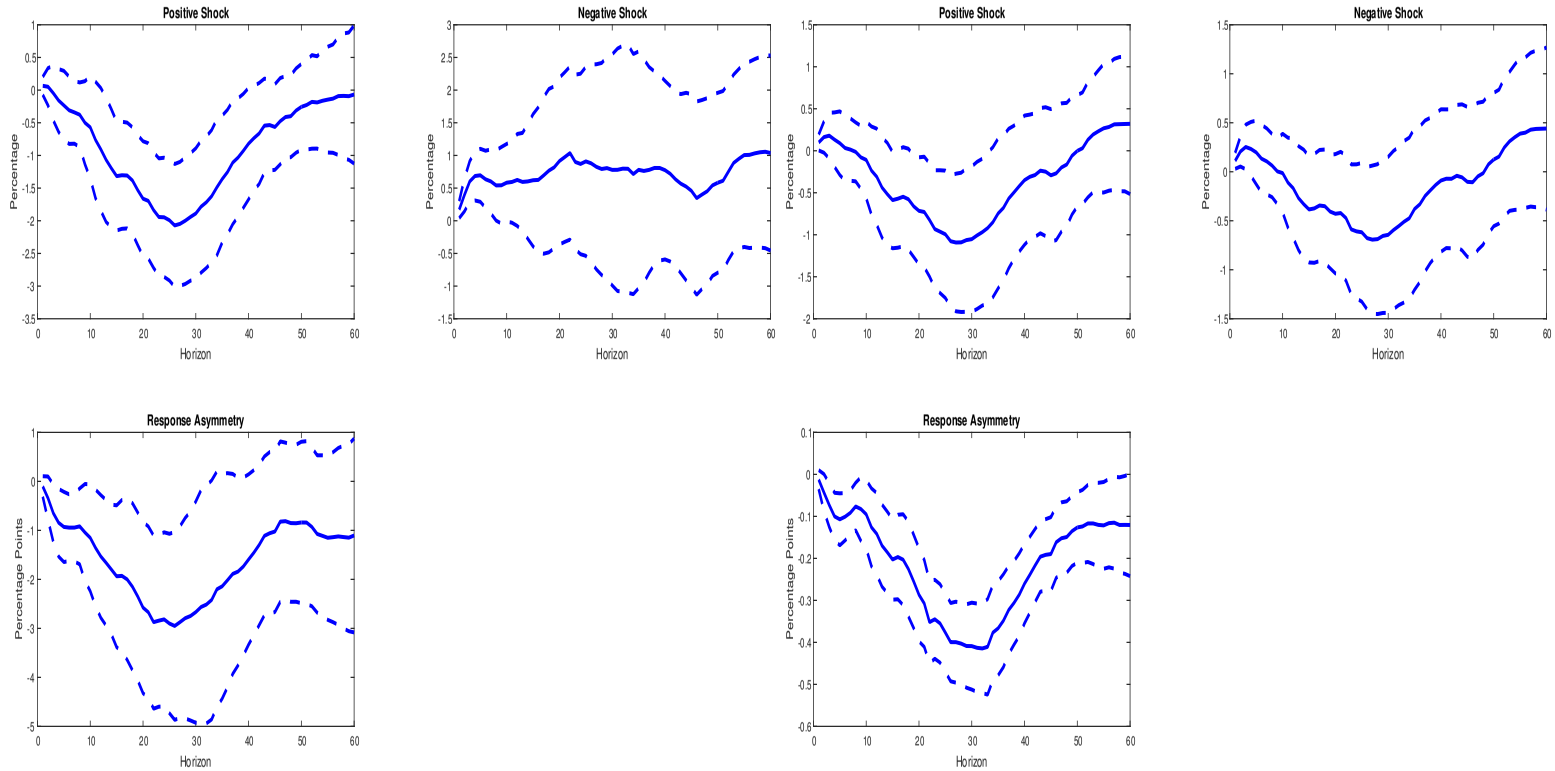


(a) The Estimated Sign-Dependent Impulse Responses and 97.5th and 2.5th Percentile Bands.

(b) The Estimated Sign-Dependent Impulse Responses and 97.5th and 2.5th Percentile Bands.

Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regressions (9) and (10) where the outcome variable is logged industrial production and the credit supply shock is measured as the residual of a regression of EBP on 12 own lagged values and squared values as well as 12 lags of the log-first-differences of the real S&P 500 index. Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the estimated impulse response from estimating Regression (9) and the dashed lines are the 97.5th and 2.5th percentile bands. Panel (b): The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 4: **Sign-Dependent Impulse Responses to Monetary Policy Shocks: (a) Dichotomous Specification; (b) Second-Order Specification.**

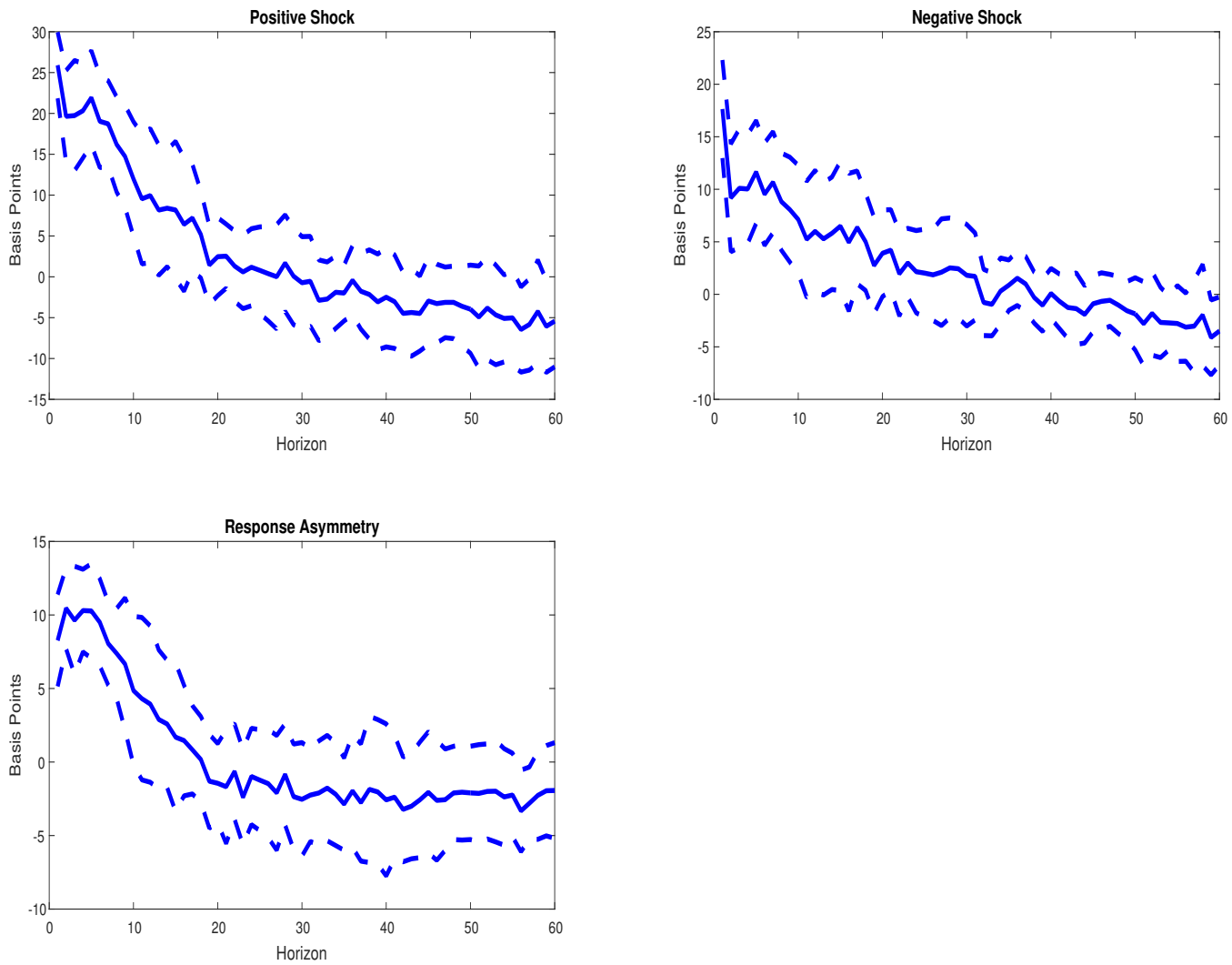


(a) The Estimated Sign-Dependent Impulse Responses and 97.5th and 2.5th Percentile Bands.

(b) The Estimated Sign-Dependent Impulse Responses and 97.5th and 2.5th Percentile Bands.

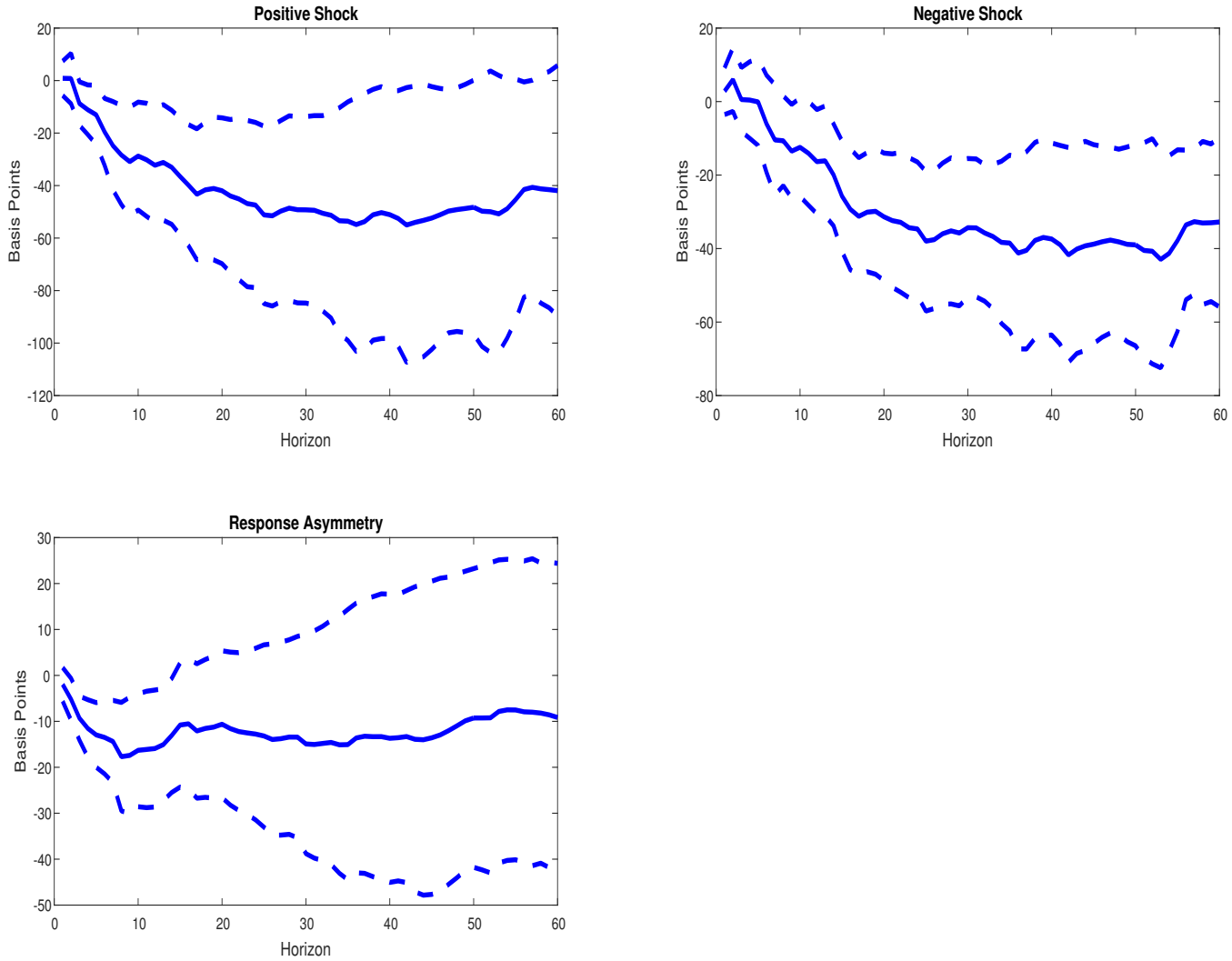
Notes: This figure presents the impulse response asymmetry for monetary shocks from applying an LP-based estimation of Regressions (9) and (10) where the outcome variable is logged industrial production and the monetary policy shock is the extended Romer and Romer (2004) shock series (spanning 1969:M1-2007:M12) constructed by Wieland and Yang (2016). Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the estimated impulse response from estimating Regression (9) and the dashed lines are the 97.5th and 2.5th percentile bands. Panel (b): The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 5: **Sign-Dependent Impulse Responses of Excess Bond Premium to Credit Supply Shocks**.



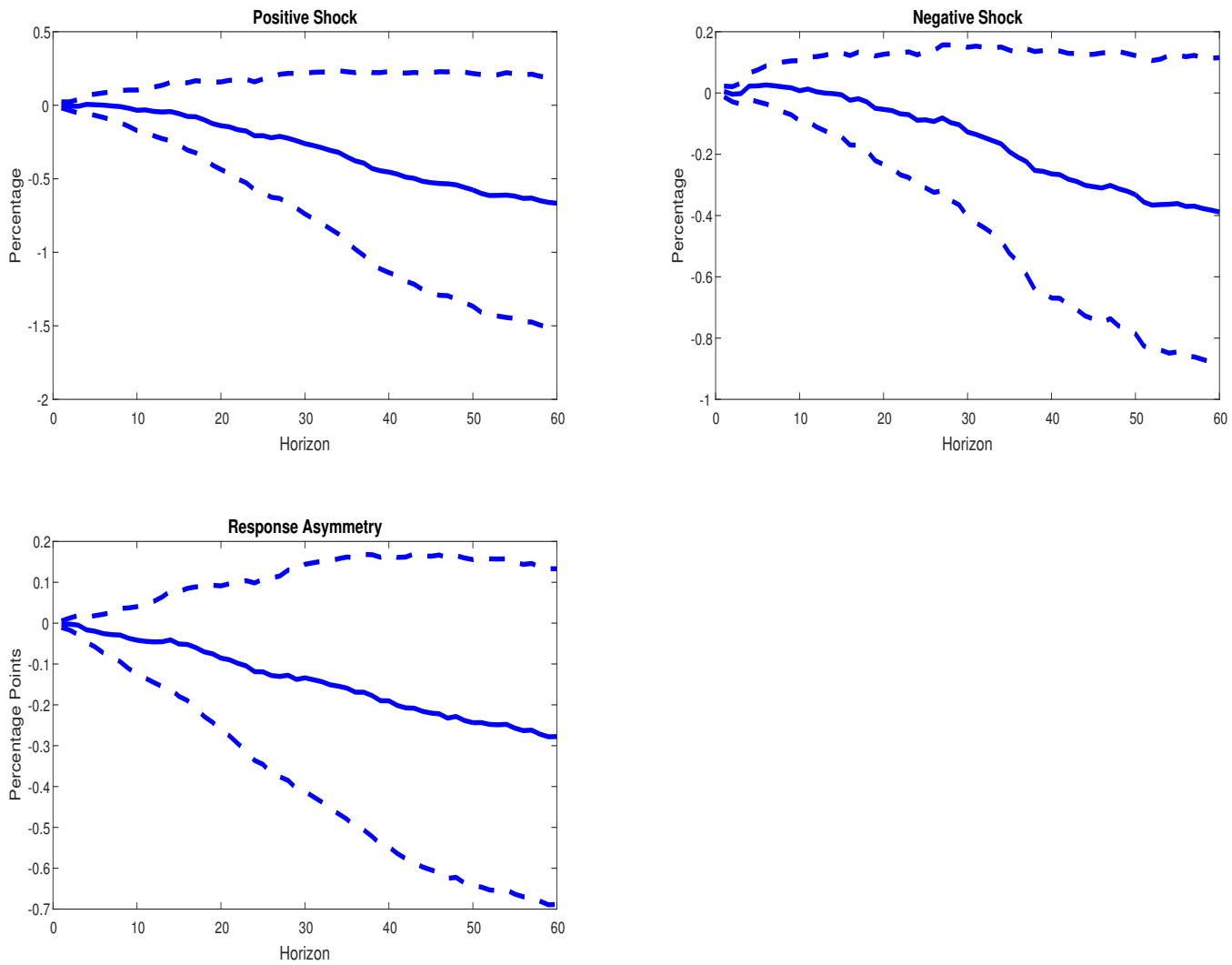
Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regression (10) where the outcome variable is the excess bond premium (EBP) variable from Gilchrist and Zakrajek (2012) and the credit supply shock is measured as the residual of a regression of EBP on 12 own lagged values and squared values as well as 12 lags of the log-first-differences of the real S&P 500 index. Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 6: **Sign-Dependent Impulse Responses of Federal Funds Rate to Credit Supply Shocks**.



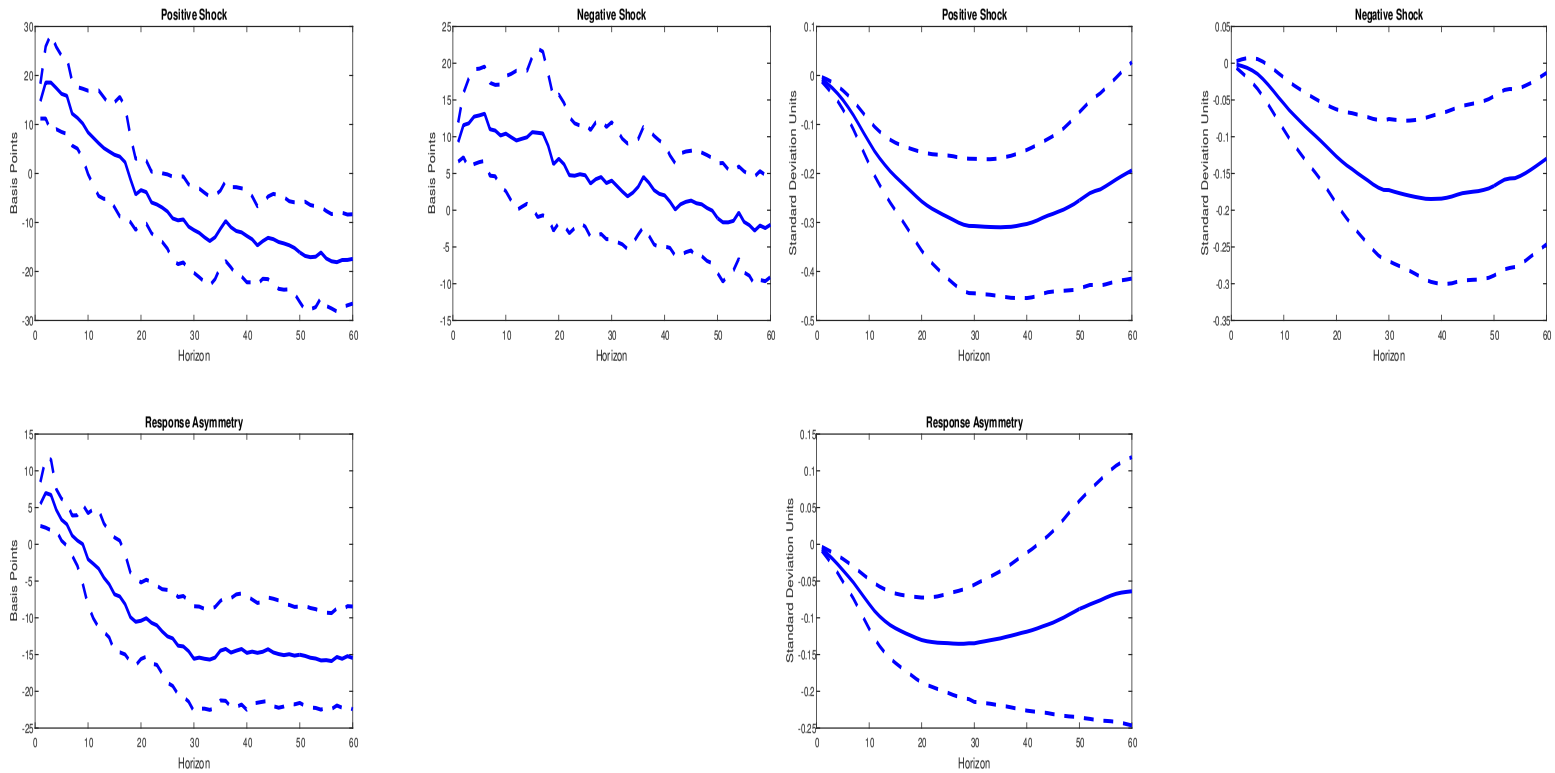
Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regression (10) where the outcome variable is the effective federal funds rate and the credit supply shock is measured as the residual of a regression of EBP on 12 own lagged values and squared values as well as 12 lags of the log-first-differences of the real S&P 500 index. Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 7: **Sign-Dependent Impulse Responses of Nominal Hourly Wage to Credit Supply Shocks**.



Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regression (10) where the outcome variable is the logged average hourly earnings of production and nonsupervisory Employees in the private sector and the credit supply shock is measured as the residual of a regression of EBP on 12 own lagged values and squared values as well as 12 lags of the log-first-differences of the real S&P 500 index. Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 8: **Sign-Dependent Impulse Responses to Credit Supply Shocks: (a) Credit Spread; (b) Non-Financial Leverage.**

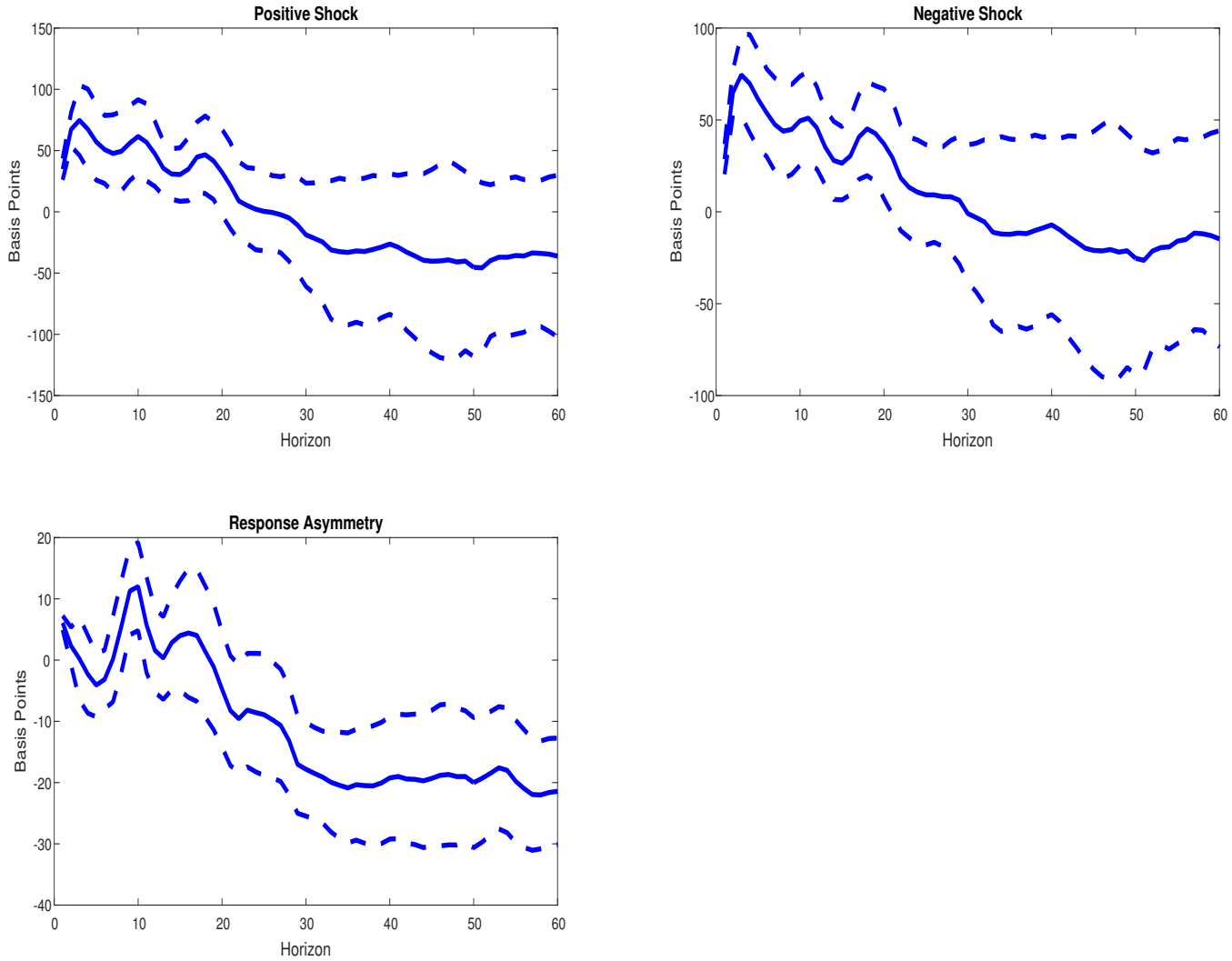


(a) The Estimated Sign-Dependent Impulse Responses of Credit Spread and 97.5th and 2.5th Percentile Bands.

(b) The Estimated Sign-Dependent Impulse Responses of Non-Financial Leverage and 97.5th and 2.5th Percentile Bands.

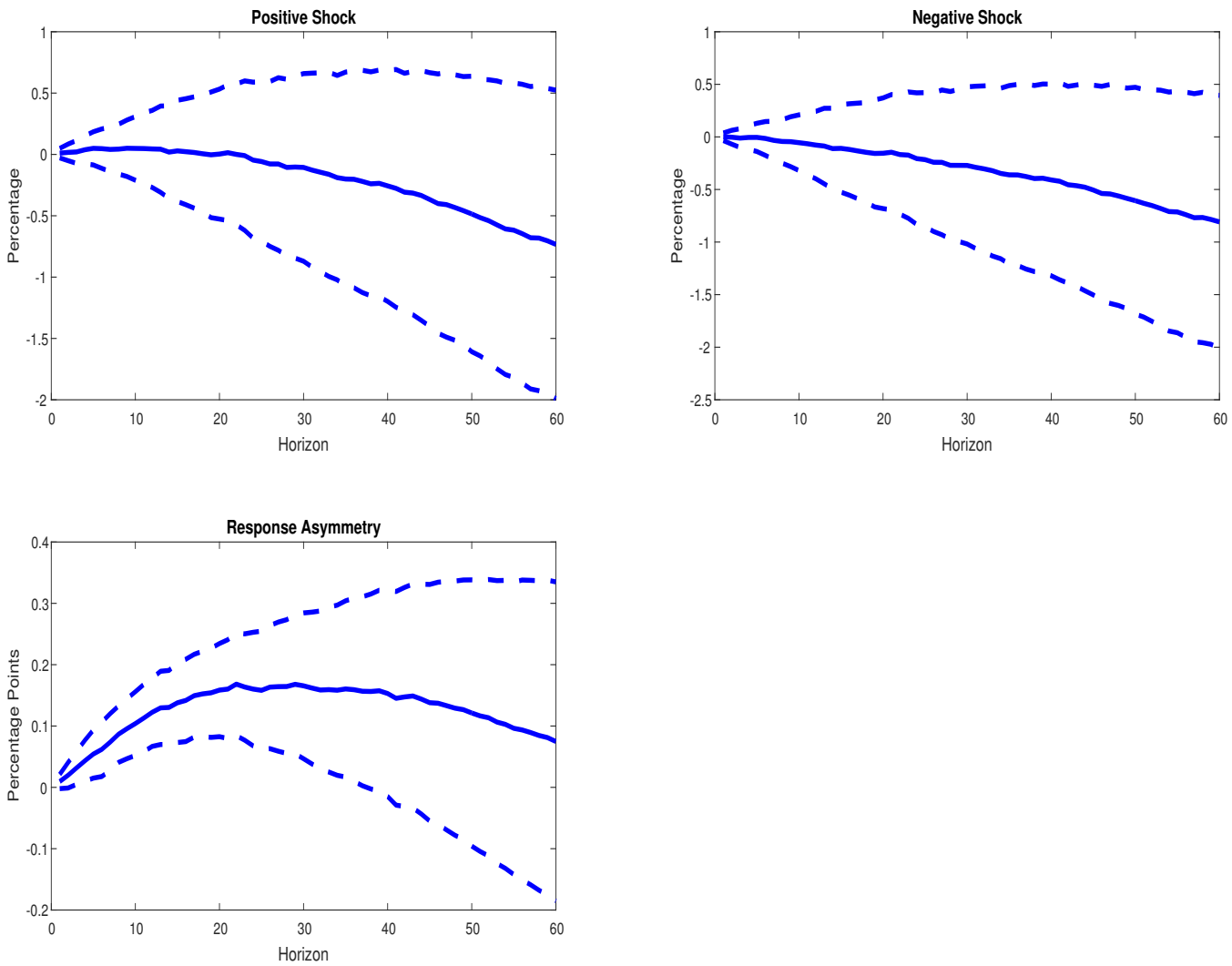
Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regression (10) where the outcome variables are the credit spread from Gilchrist and Zakrajek (2012) (panel (a)) and the Chicago Fed nonfinancial leverage index. The credit supply shock is measured as the residual of a regression of EBP on 12 own lagged values and squared values as well as 12 lags of the log-first-differences of the real S&P 500 index. Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 9: **Sign-Dependent Impulse Responses of Federal Funds Rate to Monetary Policy Shocks**.



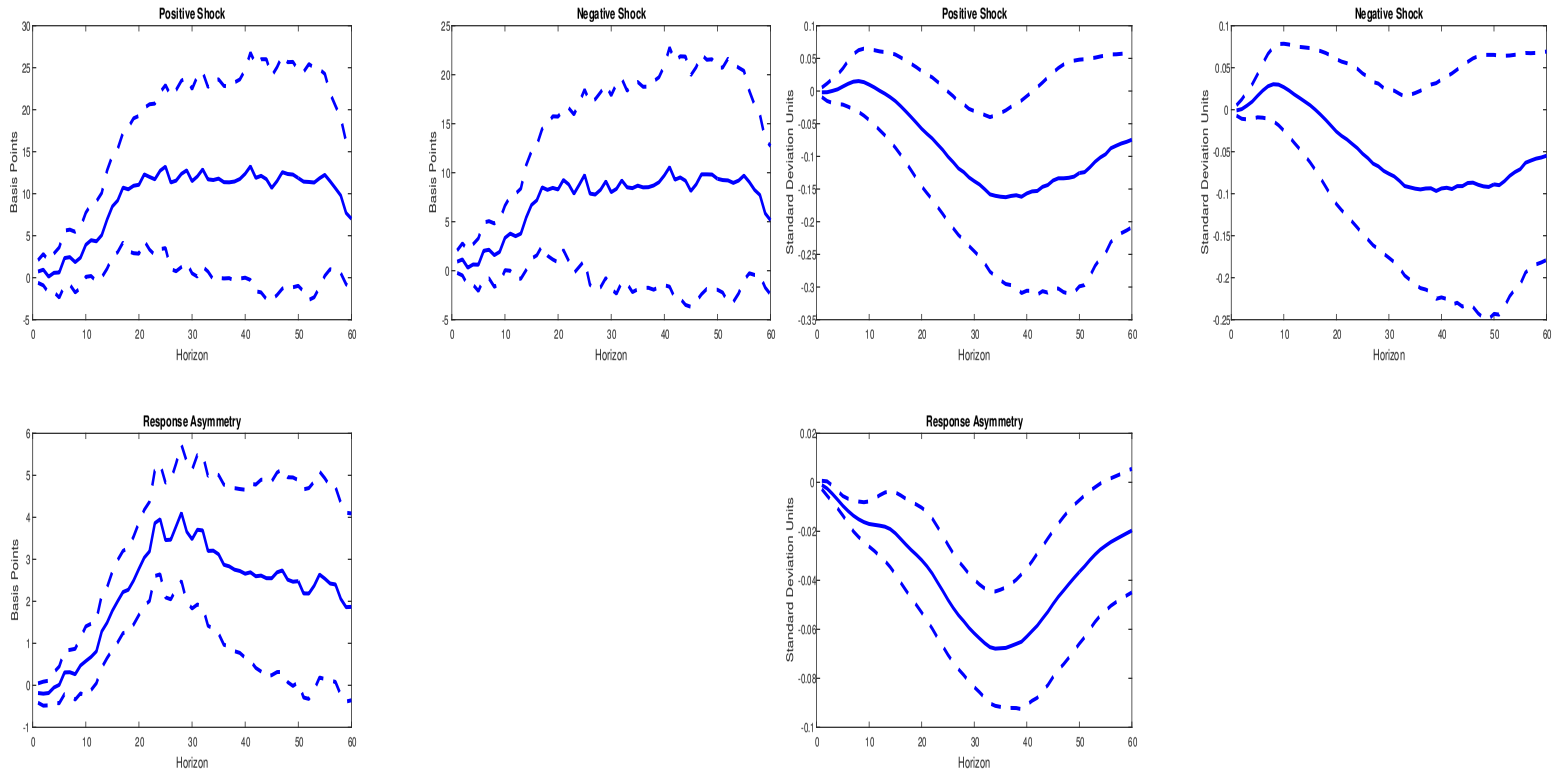
Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regression (10) where the outcome variable is the effective federal funds rate and the monetary policy shock is the extended Romer and Romer (2004) shock series (spanning 1969:M1-2007:M12) constructed by Wieland and Yang (2016). Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 10: **Sign-Dependent Impulse Responses of Nominal Hourly Wage to Monetary Policy Shocks**.



Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regression (10) where the outcome variable is the logged average hourly earnings of production and nonsupervisory Employees in the private sector and the monetary policy shock is the extended Romer and Romer (2004) shock series (spanning 1969:M1-2007:M12) constructed by Wieland and Yang (2016). Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. Panel (a): The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 11: **Sign-Dependent Impulse Responses to Monetary Policy Shocks: (a) Credit Spread; (b) Non-Financial Leverage.**

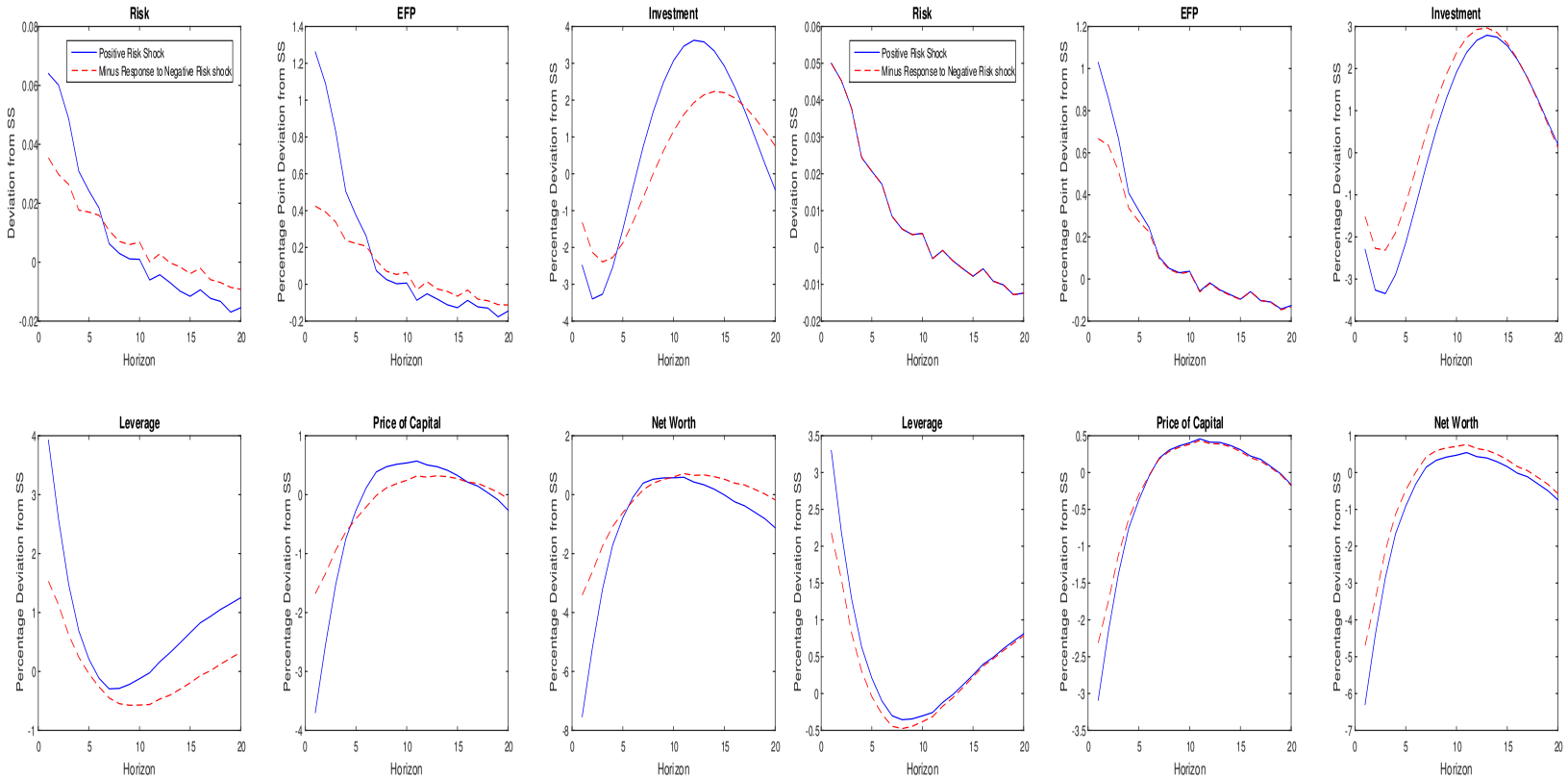


(a) The Estimated Sign-Dependent Impulse Responses of Credit Spread and 97.5th and 2.5th Percentile Bands.

(b) The Estimated Sign-Dependent Impulse Responses of Non-Financial Leverage and 97.5th and 2.5th Percentile Bands.

Notes: This figure presents the impulse response asymmetry for credit supply shocks from applying an LP-based estimation of Regression (10) where the outcome variables are the credit spread from Gilchrist and Zakrajek (2012) (panel (a)) and the Chicago Fed nonfinancial leverage index. The monetary policy shock is the extended Romer and Romer (2004) shock series (spanning 1969:M1-2007:M12) constructed by Wieland and Yang (2016). Shown impulse responses are with respect to one standard deviation positive/negative shock. The response asymmetry estimates are defined as the difference between the positive shock's effects and the negative shock's effect. The solid line is the estimated impulse response from estimating Regression (10) and the dashed lines are the 97.5th and 2.5th percentile bands.

Figure 12: **Sign-Dependent Responses Risk: (a) Accounting for Exogenous Sign-Dependence; (b) Shutting Down Exogenous Sign-Dependence**.



(a) Sign-Dependent Impulse Responses to Risk Shocks (Accounting for Stronger Persistence of Negative Shocks).

(b) Sign-Dependent Impulse Responses to Risk Shocks (Shutting Down the Stronger Persistence of Negative Shocks).

Notes: Panel (a): This figure presents the impulse responses to a positive and negative risk shock from the model presented in Appendix A where the exogenous process for risk assumes a second-order moving average process that admits the coefficients implied by the sign-dependent responses of EBP in the data. Panel (b): This figure presents the impulse responses to a positive and negative risk shock from the model presented in Appendix A where the exogenous process for risk is the same as that underlying Figure 12a with the only difference being that its associated asymmetry is completely shut down.

For both figures, the responses are shown in terms of percentage deviations from steady state values (except for risk and EFP, whose responses are shown in terms of raw deviation and percentage point deviation, respectively). Solid lines depict responses to a positive risk shock, whereas dashed lines present responses to a negative shock (multiplied by -1 for comparison purposes). Horizon is in quarters.