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Abstract

Existing research generally finds that the magnitude of the effect of supervisory rating shocks on real economic activity is small and short-lived. This is puzzling because corrective actions addressing weaknesses in underwriting and other practices frequently include lending restrictions and thus would be expected to have a stronger effect on real activity. As supervisory actions curb poorly underwritten or uneconomic loans, transmission of macroprudential policy throughout the macroeconomy should be evident in the dynamic responses of the real GDP and other measures of real activity. We use the local projections approach to estimate impulse responses from a vector autoregression (VAR) model. We show that the effect of supervisory stringency shocks is larger than the one estimated with the standard Cholesky structural VAR approach. We find that the effects are asymmetric: bank downgrades lead to a pronounced decline in real activity, while upgrades do not result in its increase. This would follow if the decrease is driven by poor lending practices that would not be expected to resume when the bank is upgraded. The linear framework averages out these effects, overstating the impact of upgrades, and understating that of downgrades. Furthermore, we document the presence of nonlinear effects for the downgrade shocks, as their impact increases disproportionately with its size. Such effects are not observed for upgrade shocks. Finally, we demonstrate that our results are robust to the inclusion of a variety of controls and additional endogenous variables.

JEL Classification: G21; E32; E37.
Keywords: CAMELS ratings; vector autoregression; local projections; asymmetries; macroprudential policy; real activity.

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1 Introduction

Bank regulators face an inherent tradeoff in their objective of effective supervision of the banking system. On one hand, they seek to maintain a stable and effective financial system, guarding against systemic risk through extensive monitoring and regulatory enforcement. On the other hand, they recognize that such actions can have unintended consequences in the banking sector and hence may be detrimental for economic activity.

The extent to which regulatory oversight negatively affects economic growth in the short or long run is an empirical question. Early evidence indicates that intensified enforcement of capital regulations and supervisory standards contributed to a tightening of credit, thereby causing a contraction in economic activity Peek & Rosengren (1995) and Peek *et al.* (2003). Subsequent research, however, suggests that the effects tend to be temporary (Bassett *et al.* (2012)), inconsistent over time and over different loan categories (Curry *et al.* (2008), Ramirez & Fissel (2013)), and the magnitude of the effect appears to be relatively small (Berger *et al.* (2001)). The fact that the effects seem to be uneven, sensitive to time periods and across loan categories suggests that the relationship is inherently nonlinear.

Nonlinearities and asymmetric variations in the effects of supervisory policy actions on output are challenging to model using standard time series techniques, such as traditional vector autoregressions. Recent advances in time series econometrics, however, have made significant inroads into modeling of these aspects of the data. In this study, we apply the local projections methodology proposed by Jorda (2005) for estimating the effect of regulatory toughness in the presence of asymmetries and nonlinearities.

To identify the effect of regulatory oversight accurately, it is important to observe variations in supervisory policy actions that are not correlated with economic activity. Changes in regulatory oversight may be associated with changes in the banking systems financial health. But if regulatory changes are driven by shocks in macroeconomic conditions, the observed association between regulatory oversight and banking conditions may just be a reflection of a worsening in economic activity, rather than a causal relationship between regulatory oversight and banking conditions.

Our empirical framework is semistructural. We explore the extent to which variations in bank supervisory shocks affect economic activity in dynamic macroeconometric models imposing the Choleski orthogonalization on the residual variance-covariance matrix to identify structural shocks. As indicated above, we go beyond the standard VAR modeling approach and allow for nonlinear and asymmetric effects to be present. Our results indicate that these features are indeed important in the data and, therefore, need to be modeled for an accurate understanding of the effect of macroprudential policy on measures of economic activity. We find that downgrades lead to a decline in real GDP growth and an increase in unemployment, while upgrades do not produce statistically significant changes in these variables. Differences in responses to shocks of different sizes suggest that nonlinearities are important for understanding the transmission mechanism of supervisory shocks: larger downgrades produce the most statistically and—on a size-adjusted basis—economically significant results, whereas larger upgrades are the least significant. One possible explanation for this asymmetry is that downgrades curb lending to firms that would otherwise would qualify for credit prior to supervisory action, whereas upgrades follow banks' abandoning risky lending practices that are not resumed following the rating change.

Our findings have several important implications. First, they can help explain the inconsistency of the results reported in the literature mentioned above. If the direct effect of regulatory actions is nonlinear, aggregate macroeconomic effects would be detectable only when the shock is particularly severe. Second, they help explain the unevenness of the effect reported in the literature, especially when studied at the aggregate level, as in Peek *et al.* (2003) and Berger *et al.* (2001). Finally, it is worth pointing out that while our results indicate that exogenously severe downgrades lead to a decline in economic activity, they do not necessarily imply that examiners ought to modify their supervisory standards and become more lenient on financial institutions. Without a comprehensive, general equilibrium analysis of the cost and benefits of macroprudential policy, this inference would be at best speculative. If the long-term benefits of the current supervisory standards, for instance in terms of promoting financial stability, outweigh their costs, it would not be desirable from a social welfare perspective to alter them.

The rest of the paper is organized is follows. The next section provides context for our work by means of a brief overview of the relevant literature. Section 3 discusses the data, with an emphasis on the construction of the aggregate CAMELS rating series. Section 4 presents the estimation framework. Section 5 discusses empirical results. Section 6 offers concluding remarks.

2 Literature Review

While there is a vast literature that investigates the interplay of the banking sector and real activity, few studies focus on the role of supervisory ratings in this process. Peek & Rosengren (1995) were among the first to use supervisory CAMELS ratings to investigate the extent to which stringency affects bank lending operations. They find that the large decline in the growth rate of bank lending in New England in the 1990s was partly driven by the strict enforcement of capital requirements. Bizer (1993) also presents evidence suggesting that worse CAMELS ratings seem to reduce bank lending. Peek *et al.* (2003) identify loan supply shocks by using the fraction of banks that have a CAMELS 5, i.e. worst, rating. They conclude that banks that receive this rating change their lending behavior quite considerably. In addition, they find that the GDP growth forecast errors are correlated with this instrument for loan supply shocks. According to their paper, part of the effect may operate through inventory investment, which tends to be heavily bank dependent. Berger *et al.* (2001) use CAMELS ratings to examine the following issues: (1) the extent of supervisor stringency with bank evaluations during the 1989-92 credit crunch period, (2) the extent of their leniency in the 1993-98 recovery period, and (3) whether these changes had any measurable impact on bank lending behavior. They find that, although bank examiners had been harsher during the credit crunch period than afterwards, these changes in the intensity of supervisory reviews had a relatively small effect on bank lending practices.[1]

Using state-level data, Curry *et al.* (2008) investigate the extent to which unexpected downgrades affect state economic conditions. They find that when supervision is excessively stringent, aggregate loan growth is adversely affected. However, the results are sensitive to the time period being considered—downgrades seem to have affected economic growth during the 1985-1993 period, but less so during the 1994-2005 period. They attribute this change to the fact that supervisory oversight was not as stringent in the second period as it was on the first.

Using bank-level data, Ramirez & Fissel (2013) investigate whether bank supervision has an effect on lending behavior. They examine three different loan categories (commercial and industrial loans, real estate loans, and consumer loans), allowing for asymmetric effects (downgrades versus upgrades). They find strong evidence for an asymmetric effect: unanticipated downgrades have a long-lasting adverse effect on loan growth, but upgrades do not affect lending behavior. Although they do not investigate the transmission of macroprudential shocks to real activity, their results lend credibility to the lending channel of such transmission that we have presented in the previous section: tighter lending standards that follow supervisory downgrades curb riskier lending activity and lead to macroeconomic contractions, whereas

[1] Krainer & Lopez (2009) reach a similar conclusion using the BOPEC ratings assigned to bank-holding companies. For a discussion of differences and similarities between CAMELS and BOPEC ratings, see Krainer & Lopez (2004) or Krainer & Lopez (2008).

upgrades do not necessarily make banks resume riskier forms of lending practices.

Similarly, Kiser *et al.* (2012) examine whether changes in CAMELS ratings of small banks (less that $5 billion in assets) affected loan growth between 2007 and 2010. They find that, after controlling for a wide range of factors, downgraded banks reduced their lending by 5 to 6 percent. However, just as Ramirez & Fissel (2013), they do not investigate whether such downgrades affect aggregate economic activity. Bassett *et al.* (2012) develop a model that predicts CAMELS ratings based on an extensive array of bank-specific financial ratios, as well as local economic conditions over the 1991 to 2011 period. They then use a measure of supervisory stringency (based on CAMELS ratings) and use a VAR model to investigate whether it has any effect on aggregate economic activity. Their VAR results suggest a decline of about 0.4 percent after about 1 year. Although their model investigates the impact of supervisory stringency up to 20 quarters ahead, they find the effects cease to be statistically significant after about four to five quarters.

In the next section, we detail our construction of an aggregate CAMELS measure and discuss the set of control variables that may affect our macroprudential shock identification strategy. We contrast the results from VAR and local projections and discuss the role that asymmetries and nonlinearities may play in the transmission of macroprudential shocks.

3 Data

In this section, we briefly overview our empirical strategy to motivate our selection of different banking and macroeconomic variables; we provide a more rigorous account of this strategy in the subsequent section. All data are quarterly and cover the sample period from 1984q1 to 2013q4. Our main focus is on the dynamic interaction between supervisory ratings and measures of real activity but we do allow for a large number of control variables to test the robustness of our baseline results.

3.1 CAMELS Rating

CAMELS ratings are a point-in-time assessment of all significant financial and operational factors related to six key components of bank health: (C)apital adequacy, (A)sset quality, (M)anagement capability, (E)arnings, (L)iquidity, and market risk (S)ensitivity . These ratings are generated using a combination of financial ratios and examiner judgement. While each component gets a rating from 1 (best) to 5 (worst), there is also a composite CAMELS rating to assess the overall health of the institution. Therefore, a downgrade in this rating sends the message that the bank's financial condition has worsened. If the downgrade is severe enough, to a score of 4 or 5, the bank's management must take corrective action.[2] Figure 1 describes the historical evolution of the distribution of CAMELS composite ratings across banks.

CAMELS ratings are assigned during an on-site bank examination that can vary in scope and purpose. Examinations are conducted every 12-18 months and every 6 months for weaker banks. The duration of an examination can range anywhere from about a month to more than one year; the latter occurs in large and complex institutions. Based on these facts, examiners from either the federal or state regulators are in roughly 20-30 percent of all banks in any given quarter. Our measure of the supervisory stance described below relies only on these newly assigned ratings. Figure 2 tracks the cross-sectional distribution of the frequency[3] of assignment of new CAMELS ratings over time, with quarters since last assignment on the vertical axis. (Hence 0 implies that ratings were assigned in consecutive quarters, 1—skipping one quarter, and so on.) Hirtle & Lopez (1999) discuss the implementation of the FDIC Improvement Act of 1991 and its effect on the process of assigning CAMELS ratings. The Act required that full-scope, on-site examinations be conducted at banks at least every year. The idea was that more frequent examinations could allow regulators to address emerging problems quicker and reduce the risk and magnitude of loss to the deposit insurance fund and, ultimately, taxpayers. Well capitalized and well managed small institutions (around \$100 million in assets) were granted an exception where exams were only required at least every 18 months.

This paper focuses on the composite CAMELS rating generated by full-scope examinations or problem memos prepared by the bank's primary regulator.[4] As the literature generally finds, CAMELS ratings downgrades, especially those that culminate with a 3, 4 or 5 rating, result in more conservative or restricted lending practices and potentially higher capital requirements. As a proxy for tracking supervisory strictness, we use asset-weighted average CAMELS ratings provided by the FDIC and computed over all FDIC-insured institutions as follows:

$$r_t = \frac{\sum_{i=1}^{N_t} a_{it} r_{it}}{\sum_{i=1}^{N_t} a_{it}}, \tag{1}$$

where r_{it} is the composite CAMELS rating of a given institution i at time period t, a_{it} is the size of its

[2] A CAMELS rating of 4 signals serious supervisory concern, whereas a rating of 5 implies critically deficient performance associated with impending failure.

[3] The quarters since last exam was capped at 20 quarters. These outliers were generally due to inactive bank charters that were not examined.

[4] Primary regulators include the Federal Reserve Board, the Office of the Comptroller of Currency, the Office of Thrift Supervision (up until 2011), the Federal Deposit Insurance Company, or a state regulatory authority.

assets, and N_t is the number of banks in the industry whose dynamics may also be gleaned from Figure 1.

Figure 3 describes the evolution of changes in the asset-weighted average CAMELS rating, $\triangle r_t$—our measure of macroprudential policy stance—during our sample. To provide a sense of the magnitude of shocks considered in the empirical models below, we measure them in terms of the standard deviations of our measure, $\sigma_{\triangle r}$. We note that while a change of three standard deviations in our measure has only happened during the most recent crisis, a change of two standard deviation levels occured several times: downgrades in the early 1990s and 2000s, upgrades in the mid-1990s.

3.2 Measures of Real Activity and Macroeconomic Controls

All macroeconomic variables are from the FRED2 database maintained by the St. Louis Federal Reserve. We use two measures of real activity: real GDP growth and change in the unemployment rate.[5] Figure 3 describes their evolution. Our robustness checks include the following macroeconomic variable controls: annualized percentage change in the GDP deflator (inflation rate); federal funds rate; term spread, defined as the difference between the 10-year Treasury yield, and the 3-month T-bill yield; annualized percentage change in the all-transactions house price index (HPI); annualized percentage change in the real S&P500 stock price index obtained from Robert Shiller's website; University of Michigan Index of Consumer Sentiment; and the spread between the 30-year mortgage rate and the 3-month T-bill yield. We include concurrent values of these variables and up to P of their lags, whose specific value is discussed below. We designate this set of control variables by 'X1'.

3.3 Banking Controls

Following Bassett *et al.* (2012), we construct a set of banking variables that reflect industry-wide conditions. These data are from the FDIC Quarterly Banking Profiles and include the following:

- **Capital Adequacy**: Leverage ratio (Tier 1 leverage capital normalized by total assets);
- **Asset Quality**: noncurrent loan ratio (all loans and leases past due and in nonaccrual status normalized by total assets), ratio of noncurrent loans to reserves for losses, ratio of loans secured by

[5] A previous version of the paper also considered change in total capacity utilization, the industrial production index growth, and growth in its manufacturing subcomponent. The results for all three were fairly similar and fell in between those for the real GDP growth and the unemployment rate change in terms of magnitude and statistical significance.

real estate to total assets, ratio of commercial and industrial loans to total assets, ratio of loans to other depository institutions to total assets;

- **Management Capability**: Ratio of noninterest expense to total revenue;
- **Earnings**: Return on assets (ROA, net income normalized by total assets), net interest margin (NIM);
- **Liquidity**: Ratio of securities, federal funds sold, and reverse repurchase agreements to total assets, ratio of brokered deposits to total assets;
- **Sensitivity to Risk**: Return on risky assets, defined as noninterest income net of deposit fees and fiduciary income divided by total assets

Since these variables take up a relatively large number of degrees of freedom and change quite slowly, we include only their concurrent values. We designate this set of control variables by 'X2'.

3.4 Survey of Professional Forecasters Controls

Following Bassett *et al.* (2014), who study the effect of changes in bank lending conditions on the macroeconomy, we also control for expectations of the future macroeconomic conditions. We obtain the mean values from the Survey of Professional Forecasters available from the Federal Reserve Bank of Philadelphia website and contruct one-year-ahead projections for the following variables (transformation of original series): real GDP (growth rate); inflation rate as measured by the GDP deflator (growth rate); corporate profits (growth rate); unemployment rate (change); housing starts (growth rate); Treasury bill yield (change). We designate this set of control variables by 'X3'. Table 1 provides a summary of the types of variables that enter each set of control variables.

4 Estimation Framework

Our empirical analysis of the interplay of changes in CAMELS ratings and measures of real activity proceeds in four steps. First, we study the standard structural vector autoregression (SVAR) approach that relies on the Cholesky decomposition of the variance-covariance matrix of residuals to provide a comparison benchmark for the local projection results. Second, we adopt the local projection approach of Jorda (2005) in the linear setting as the closest comparison with the SVAR framework. Third, we introduce nonlinear terms into the local projections framework that allows us to evaluate asymmetries and nonlinearities in the transmission of shocks to CAMELS ratings to real activity. Finally, in all three cases, we consider the impact of augmenting the empirical models with alternative sets of exogenous control variables described above.

4.1 Standard Vector Autoregression

The standard approach to estimating vector autoregressive (VAR) models (see Hamilton (1994) or Lutkepohl (2007), for extensive methodological overviews) begins with an ordinary least squares estimation of the following system:

$$\mathbf{y_t} = \alpha + \sum_{p=1}^{P} \mathbf{B_p} \mathbf{y_{t-p}} + \mathbf{D}\mathbf{x_t} + \mathbf{u_t}, \tag{2}$$

where $\mathbf{y_t}$ is the $T \times K$ matrix of dependent variables, $\mathbf{B_p}$ are matrices of coefficients associated with different lags up to order P, and $\mathbf{u_t}$ are reduced-form residuals. A popular alternative for the identification of structural shocks is the Cholesky orthogonalization of the variance-covariance matrix of $\mathbf{u_t}$, $\mathbf{B_0}$. The impulse response of $\mathbf{y_t}$ to structural shocks $\mathbf{v_t} = \mathbf{B_0}^{-1}\mathbf{u_t}$ at horizon s, $\mathbf{\Phi_s}$, can be shown to be related to the parameters estimated in (2) by initializing $\mathbf{\Psi_0} = \mathbf{I}$ and then obtaining their values for longer horizons through the following recursion: $\mathbf{\Psi_s} = \sum_{h=1}^{s} \mathbf{\Psi_{s-h}} \mathbf{B_h}$ for $s > 0$ and where $\mathbf{B_s} = \mathbf{0}$ for $s > P$. Responses to the structural shocks $\mathbf{v_t}$ are simply obtained by the lower triangular matrix from the Cholesky orthogonalization of the reduced-form shocks: $\mathbf{\Phi_s} = \mathbf{\Psi_s}\mathbf{B_0}$. Note that the VAR model of endogenous variables $\mathbf{y}$ may include a set of exogenous controls, $\mathbf{x}$. We exclude the latter for our baseline results and conduct extensive robustness checks for different compositions of the set of exogenous variables.

4.2 Local Projections Approach—Linear Framework

Jorda (2005) proposes an alternative method for estimating such impulse response functions (IRFs) via the local projections method. A distinct advantage of this approach is the incorporation of nonlinear endogenous variable terms that can still be estimated by ordinary least squares. Its linear version is immediately comparable to the VAR setting detailed above. It entails estimating

$$\mathbf{y_{t+s}} = \alpha^{\mathbf{s}} + \sum_{p=1}^{P} \mathbf{B_p^{s+1}} \mathbf{y_{t-p}} + \mathbf{D^{s+1}} \mathbf{x_t} + \mathbf{u_{t+s}^s} \tag{3}$$

at alternative horizons $s = 0, \ldots, S$, where, again, the local-projections model may be augmented by the presence of exogenous terms, $\mathbf{x}$. Jorda (2005) then shows that impulse responses in the local projection framework are given by the coefficient matrices $\mathbf{\Psi_s} = \mathbf{B_1^s}$ while normalizing the impact response to be, again, $\mathbf{\Psi_0} = \mathbf{I}$. As in the standard VAR case, estimating responses to structural shocks requires post-multiplying $\mathbf{\Psi_s}$ by a matrix that imposes such restrictions. While, in principle, one could construct $\mathbf{B_0^s}$ for each s, in practice, established by Jorda (2005) and Kilian & Kim (2011), only the $\mathbf{B_0}$ from (2) is used for this purpose.

4.3 Local Projections Approach—Nonlinear Framework

The linear framework given by (3) can be easily extended by estimating

$$\mathbf{y_{t+s}} = \alpha^{\mathbf{s}} + \mathbf{B_1^{s+1}} \mathbf{y_{t-1}} + \mathbf{Q_1^{s+1}} \mathbf{y_{t-1}^2} + \mathbf{C_1^{s+1}} \mathbf{y_{t-1}^3} + \sum_{p=2}^{P} \mathbf{B_p^{s+1}} \mathbf{y_{t-p}} + \mathbf{D^{s+1}} \mathbf{x_t} + \mathbf{u_{t+s}^s}, \tag{4}$$

which allows for quadratic and cubic terms in $\mathbf{y}$ whose effect is stored in coefficient matrices $\mathbf{Q_1^s}$ and $\mathbf{C_1^s}$, respectively, whose initial impact matrices, $\mathbf{Q_1^0}$ and $\mathbf{C_1^0}$, are normalized to zero. Impulse response functions at time t and horizon s in response to a set of structural shocks summarized in the column vector d are now given by:

$$\mathbf{\Phi_s}(f) = \frac{1}{f} \hat{\mathbf{\Gamma}}_{\mathbf{s}} \Lambda, \tag{5}$$

where $\hat{\mathbf{\Gamma}}_{\mathbf{s}} = [\hat{\mathbf{B}}_{\mathbf{1}}^{\mathbf{s}}\ \hat{\mathbf{Q}}_{\mathbf{1}}^{\mathbf{s}}\ \hat{\mathbf{C}}_{\mathbf{1}}^{\mathbf{s}}]$, $\Lambda = [d;\ 2y_{t-1}d + d^2;\ 3y_{t-1}^2 d + 3y_{t-1}d^2 + d^3]$ and d is the impact vector that is a function of the size of a structural shock, f, discussed below. Note that in principle different values of y_{t-1} may affect the impact of nonlinearities on variables' impulse responses. To keep the results as comparable to the linear framework as possible and impulse response matrices time-invariant, we set $y_{t-1} = \bar{y}_{t-1}$. Formation of the 95% confidence intervals for impulse responses is achieved by applying $\pm 1.96 \Lambda' \hat{\mathbf{\Sigma}}^{\mathbf{s}} \Lambda$ to the point estimates, where $\hat{\mathbf{\Sigma}}^{\mathbf{s}}$ is the HAC-adjusted variance-covariance matrix of $\hat{\mathbf{\Gamma}}_{\mathbf{1}}^{\mathbf{s}}$ estimates.

Each of our measures of economic activity is ordered first and changes in CAMELS ratings are ordered second, reflecting the assumption that CAMELS rating changes respond immediately to real activity shocks, whereas real activity responds to CAMELS shocks with a lag.[6] Setting the shock vector $d = \tilde{\mathbf{B}}_{\mathbf{0}}[0\ f]'$, where $\tilde{\mathbf{B}}_{\mathbf{0}}$ is the same as $\mathbf{B_0}$ with the bottom right element replaced with $\sigma_{\triangle r}$ to ensure that the size of the shock stays the same across different empirical specifications and $f = [1,\ 2,\ 3]$ describes the factor applied to one standard deviation of the structural shock to CAMELS rating. Dividing the resulting impulse responses by the size of the factor then allows to gauge the impact of nonlinearities. In the linear case, they will be identical for any value of f. Importantly, in the baseline specifications, (2), (3), and (4) are estimated with the restriction that $\mathbf{D} = \mathbf{0}$, i.e. without controls, whereas our robustness checks relax that assumption.

5 Empirical Results

We next explore the differences in empirical results delivered by alternative approaches. We first compare the linear results in the bivariate setting. Then we move to the nonlinear setting. Finally, we consider the effect of augmenting the models' with exogenous control variables.

5.1 Baseline Models: Local Projections vs. VAR Impulse Response Functions

We first compare the performance of linear models for local projection (LP) and standard Cholesky SVAR approaches to generating impulse responses in models where a measure of real activity is placed first and is the exogenous variable and the CAMELS rating change is the endogenous variable. For SVAR, we construct confidence intervals using 10,000 replications from a bootstrap proposed by Kilian (1998). Kilian & Kim (2011) evaluate the performance of bootstrapped and asymptotic confidence intervals and find that whereas bootstrapping methods deliver superior results in the VAR setting, asymptotic confidence intervals have better coverage properties for the local projection counterpart and are similar to the VAR bootstrap. For this reason, we proceed with asymptotic confidence intervals for local projection estimation detailed above.

The main reason for our choice of the local projections approach is its ability to accommodate nonlinearities easily. Another reason is its relative parsimony. Although both Schwartz and Akaike information criteria select only 1 lag for the two baseline VAR models, it appears that uncovering the full effect of the CAMELS shock on real activity requires a larger number of lags. Figure 5 presents the results from the

[6] Our results are robust to switching the ordering in the Choleski identification.

model where the real GDP growth is the measure of real activity, with LP specification estimated with only one lag.[7] This figure demonstrates that, as the lag length in the VAR model increases, its mean impulse response estimate converges to its LP counterpart, with the early impact being somewhat smaller and less statistically significant and the maximum impact occurring a bit later. Figure 6 presents a similar set of results where the measure of real activity is the change in the unemployment rate. Again, the VAR impulse response converges to the LP one only after a much larger number of lags than selected by the information criteria is added to the model and the peak response occurs about a quarter later.

While these results suggest that the local projection framework uncovers large and statistically significant responses of real activity to supervisory stringency shocks in an econometrically parsimonious fashion, its linear nature treats both downgrades and upgrades shocks symmetrically and does not allow for differential effects of shocks of different sizes. We relax this restriction in the following subsection.

5.2 Asymmetries and Nonlinearities in the Baseline Model

We now explore the possibility that supervisory shocks of different signs and sizes may have differential effects. To study the possible effect of asymmetries, we compare the effects of a positive (downgrade) supervisory shock to the *negative* of the negative (upgrade) one. This last transformation provides for an easy visual comparison of impulse responses and their confidence intervals: If they are identical, as is the case in the linear setting, then an asymmetry is absent and the corresponding graphs in the left and right *columns* will be the same. We also multiply the shocks rescaled by one standard deviation of the changes asset-weighted CAMELS rating, $\sigma_{\triangle r}$, by factors of two and three and then divide the resulting impulse response by that same factor to investigate the possibility of nonlinearities, as suggested by equation (5). In the linear case, such transformations would yield impulse responses and confidence intervals identical to the one standard deviation shock and the graphs in each *row* will be identical. Departures from that benchmark signal the presence of nonlinearities.

Figure 7 provides the results for the models where the real GDP growth is the measure of real activity. In each case, the confidence intervals associated with the nonlinear specification are wider than in the linear case, since the former requires estimating more coefficients, leaving fewer degrees of freedom. Impulse responses due to positive shocks (downgrades) become larger and more statistically significant as f increases

[7] Additional lags in the LP specification have negligible effect on the estimated impulse responses, because additional lags in this approach play the role of control variables, as opposed to factoring directly into the impulse response functions in VARs.

from 1 to 3, suggesting a presence of nonlinear effects. In the case of $f = 1$, mean estimates of linear and nonlinear impulse responses are virtually indistinguishable, whereas for $f = 3$, the largest response in the nonlinear case is about 2.5 times larger than for its linear counterpart. On the other hand, nonlinear impulse responses due to negative shocks (upgrades) are insignificant and the confidence intervals widen perceptibly, as the absolute value of the negative shock increases. Furthermore, while the IRF for $f = 1$ in the nonlinear model behaves comparably to the linear case, as f increases, the impulse response gets closer to the horizontal line at zero, suggesting that the larger average upgrades of the banking industry have no effect on the real GDP growth.

Figure 8 conducts similar analysis using change in the unemployment rate as the measure of real activity. The peak of the average nonlinear impulse response due to a positive shock is about 2.5 times as large as that of its linear counterpart; once again, they become larger and more significant statistically as the magnitude of the shock becomes larger. Negative nonlinear impulse responses, on the other hand, are, on average, smaller than their linear counterparts and rapidly lose statistical significance as the magnitude of the shock increases.

In sum, the results presented in this subsection indicate that there is a strong case for the asymmetric effects of CAMELS rating changes, with downgrades leading to declines in real activity while upgrades having no effect on it. The baseline bivariate specification outcomes suggest that the effects of large downgrades are disproportionately larger than the effect of their smaller counterparts or those of upgrades. In the next subsection, we explore whether the addition of control variables affects these results.

5.3 Robustness Checks with Respect to Alternative Control Sets

One argument against the baseline bivariate specification is that while it conserves the scarce degrees of freedom, it may yield biased estimates of slope coefficients on lagged endogenous variables in (3) and (4). Another objection is that the residuals estimated in this framework may carry information influencing bank supervisors' ratings decisions, which has to be accounted for in order to obtain truly exogenous supervisory shocks. We, therefore, augment the bivariate framework with three different sets of control variables that carry potentially relevant information. These sets are described in detail in Section 3 and summarized in Table 1.

Figure 9 investigates the effect of including alternative control sets in (3). While the impact of the shocks becomes somewhat smaller and their statistical significance deteriorates, in part due to fewer degrees of freedom, the main results from the linear specification in the baseline counterparts carry through. The addition of banking controls tends to have the largest impact on the results and the addition of the SPF forecasts the smallest.

Figure 10 compares the results for the nonlinear specification in (4) with control variables to the baseline captured in Figure 7. Relative to the baseline, the effects of all shocks are somewhat smaller and their statistical significance deteriorates, with no impulse responses due to a negative shock being significant. Positive shocks to CAMELS ratings lose their statistical significance in the case of $f = 1$, but maintain it for $f = 2$ and $f = 3$; this is, large downgrades of the banking sector continue to have a negative effect on the real GDP growth. Negative (upgrade) shocks, on the other hand, are all insignificant.

Finally, Figure 11 describes similar results using the changes in the unemployment rate as a measure of real activity. Again, while the IRF estimates become somewhat smaller and the confidence intervals widen, downgrades yield statistically significant responses for $f = 2$ and $f = 3$ whereas upgrades do not.

5.4 Supervisory Rating Changes vs. Other Credit Market Shocks

Table 2 provides a summary of the results from alternative local projection model specifications, cumulating mean impulse responses 0 through 4 quarters after the shock. Baseline results follow from Figures 7 and 8. After one year, a one-standard-deviation downgrade shock reduces real output by 0.78 percent in the linear case; a three-standard-deviation downgrade shock reduces real output by 1.28 percent, after the impulse response has been divided by a factor of three for an easy comparison with the one-standard-deviation shock. In contrast, the effects of upgrade shocks decrease, relative to the the linear benchmark, as f increases, reaching an economically insignificant value of a 0.18 percent increase in real output for $f = 3$. Similar results hold for unemployment, although the effect of nonlinearities appears to be somewhat smaller than in the real output case. Downgrade shocks raise the unemployment rate after one year between 0.44 percent in the linear case and 0.67 percent in the nonlinear case with $f = 3$, whereas large upgrades reduce the unemployment rate by about 0.35 percent for $f = 3$.

Introduction of control variables into (3) and (4) moderates these results, particularly for the sets that include large numbers of current and lagged macroeconomic variables (X1) or banking controls (X2). These results are obtained using the information reflected in Figures 10 and 11. Downgrades reduce real output by about 0.4 percent in the linear case and 0.7 percent in the nonlinear ($f = 3$) case and increase the unemployment rate by 0.2 percent and 0.35 percent respectively. Upgrades, particularly for small shocks, practically lose economic significance. Augmenting the baseline specification by real-time forecasts (X3), on the other hand, leaves the results virtually unchanged for output and reduces them by about a third for unemployment. These results provide a reference point for comparison of our results against previously documented effects of credit market shocks on real activity. The latter may be categorized into two strands of literature: One where the shock emerges from the banking sector and the other that describes the effects of monetary policy shocks.

The resurgence of interest in the effect of macroprudential policy on the economy in the wake of the most recent crisis makes the comparison of supervisory rating shocks against the voluminous literature on the effect of monetary policy shocks particularly instructive, since the the latter are well understood and their effects are documented painstakingly. An exhaustive survey of the effect of monetary shocks on the macroeconomy is beyond the scope of this paper. However, a brief overview of some of the better known contributions to this literature reveals that the effects of supervisory shocks on output documented above are at least as large as those of the monetary policy shocks.[8] Christiano *et al.* (1999) suggest that a monetary contraction results in a 0.5 percent decline in output using a medium-scale VAR model. Others generally find smaller effects using a variety of appraoches. Gorodnichenko (2006) uses a reduced-rank identification strategy to obtain a decline of 0.1 percent. Uhlig (2005) employs VARs with sign restrictions to show that this effect does not exceed 0.2 percent. Smets & Wouters (2007) estimate it to be about 0.3 percent in the context of a New Keynesian dynamic stochastic general equilibrium (DSGE) model. One exception to this range of estimates is due to the work of Romer & Romer (2004) who adjust the evolution of the federal funds rate for the real-time forecasts of future macroeconomic variables made by the Federal Reserve staff. They then use a single-equation autoregressive distributed lag (ARDL) framework to show that the implied contraction in output is about 3 times larger than what Christiano *et al.* (1999) obtain. Coibion (2012), however, finds that these results are driven by including the reserve targeting period of 1979-1982 and opting for modeling choices that are difficult to defend on statistical grounds, such as the selection of excessively long lags unsupported by the standard lag selection criteria. Once these differences are reconciled, the effects of the Romer & Romer (2004) shocks becomes comparable to the ones reported elsewhere. Our results suggest that the response of output to the supervisory shock is towards the high end of these estimates while the rescaled nonlinear responses to downgrades are considerably stronger than

[8] All results from papers referenced in this subsection are, unless otherwise specified, in response to a one-standard-deviation shock after one year.

their monetary policy counterparts.

Similar results hold for the unemployment rate impulse responses. Christiano *et al.* (1996) show in the context of a medium-scale VAR model that the unemployment rate increases by about 0.13 percent at the lower end of the available estimates. Bernanke *et al.* (2005) provide similar estimates in the context of several variants of a factor-augmented VAR model. Building on the work of Smets & Wouters (2007) and using similar DSGE models, Gali *et al.* (2011) suggest that the unemployment rate increases by 0.15-0.27 percent, depending on the assumptions about household preferences. Again, our estimates for the effect of supervisory rating shocks appear towards the high end of this range for monetary shocks, suggesting that their effect on real activity is at least as powerful.

Finally, we compare our results to other sources of credit market disturbances. In a paper most closely related to ours, Bassett *et al.* (2012) use a VAR model to show that a shock to their measure of a supervisory stringency decreases output my about 0.4%. Lown & Morgan (2006) use the Loan Officer Opinion Survey (LOOS) data to show that a tightening shock to lending standards reduces output by 0.5 percent. Also exploiting the LOOS data, Bassett *et al.* (2014) that an adverse loan supply shock reduces output by 0.6 percent. Ashcraft (2005) estimates that a percentage point increase in the ratio of failed deposits to county income leads to a 0.1 percent decrease in county income after 1 year. Therefore, the rescaled three-standard-deviation downgrade in our CAMELS rating measure roughly corresponds to a 7 percentage point increase in the ratio of failed deposits to county income.[9] The supervisory rating downgrades, therefore, appear comparable to sizeable credit market disruptions.

5.5 Controlling for Monetary Policy and Lending

Our baseline specification provides a parsimonious empirical specification that does not address the possibility that macroprudential shocks may subsume the effect of monetary policy conduct. To address this possibility, we expand the vector of endogenous variables relative to the baseline specification, inserting inflation (given by the annualized percentage change in the implicit GDP deflator), loans and leases as the percentage of bank credit, and the federal funds rate between a measure of real activity and our measure of macroprudential policy stance.[10] The empirical system, therefore, becomes a more extensive version of the standard three-variable model (real activity, inflation, federal funds rate) that has been the standard tool

[9] In the dataset used by Ashcraft (2005), the average failure involved deposits approximately equal to 10 percent of the county income.

[10] The additional macroeconomic time series are also from the FRED II database.

for analyzing the conduct of monetary policy in the United States. Since the CAMELS rating measure is ordered last, macroprudential structural shocks are orthogonal to the the reduced-form errors associated with the other endogenous variables in this framework.

Figures 12 and 13 are the five-variable counterparts to Figures 7 and 8. While the confidence intervals widen fractionally, especially due to the upgrade shocks, the mean response stay about the same as in the baseline specification, carrying over the main qualitative conclusions. One reason for the robustness of these results may be the exogeneity of our CAMELS rating measure to the macroeconomic variables included in our empirical specifications. However, we leave a detailed investigation of this possibility to future work.

6 Concluding Remarks

Investigating the degree, to which bank supervision affects economic activity, continues to be an important issue in academic circles as well as in the policy-making arena. Regulators periodically examine banks in order to ensure that the institutions are well-managed. But does exogenous variation in ratings assigned during these examinations affect aggregate economic activity? The extant literature finds that the results are mixed. The majority of the studies find that the effects of changing supervisory stringency on economic activity tends to be relatively modest and temporary. This paper argues that such conclusion may be driven by nonlinearities and asymmetries in the data.

Using a local projections technique proposed by Jorda (2005), we show that supervisory shocks indeed affect the real GDP growth and the unemployment rate change. We find that this effect is stronger for downgrades than it is for upgrades. The statistical significance of impulse responses tends to increase with the magnitude of the positive shocks and decrease with the magnitude of negative shocks, particularly after a set of exogenous control variables is introduced into the model. This finding suggests that whatever results obtain in the linear modeling framework are primarily driven by downgrades and their impact is likely to be biased downwards by failing to disentangle them from upgrades.

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A Tables

Table 1: Summary of Exogenous Variable Control Sets

Set	Type of Variables	Detailed Description	Brief Description
X1	Current and lagged macro variables	Section 4.1	Inflation, interest rates, asset returns, consumer sentiment
X2	Banking variables	Section 4.2	Leverage ratio, loan characteristics, noninterest expense ratio, ROA, NIM, liquidity ratio, return on risk assets
X3	SPF variables	Section 4.3	Year-ahead forecasts of real activity, inflation, interest, housing starts, and corporate profits

Table 2: Cumulative Impulse Responses to CAMELS Shock: Quarters 0—4

	Real GDP Growth		Unemployment Rate	
	Downgrades	Upgrades	Downgrades	Upgrades
Baseline Specification				
Linear	-0.78	0.78	0.44	-0.44
Nonlinear, $f = 1$	-0.83	0.47	0.42	-0.31
Nonlinear, $f = 2$	-1.05	0.32	0.53	-0.31
Nonlinear, $f = 3$	-1.28	0.18	0.67	-0.35
Control Set X1				
Linear	-0.42	0.42	0.21	-0.21
Nonlinear, $f = 1$	-0.32	0.08	0.09	-0.03
Nonlinear, $f = 2$	-0.50	0.03	0.19	-0.08
Nonlinear, $f = 3$	-0.73	0.01	0.35	-0.19
Control Set X2				
Linear	-0.40	0.40	0.25	-0.25
Nonlinear, $f = 1$	-0.55	0.23	0.19	-0.13
Nonlinear, $f = 2$	-0.67	0.03	0.27	-0.15
Nonlinear, $f = 3$	-0.77	-0.20	0.38	-0.21
Control Set X3				
Linear	-0.71	0.71	0.30	-0.30
Nonlinear, $f = 1$	-0.51	0.28	0.19	-0.11
Nonlinear, $f = 2$	-0.77	0.30	0.30	-0.13
Nonlinear, $f = 3$	-1.12	0.42	0.44	-0.18

B Figures

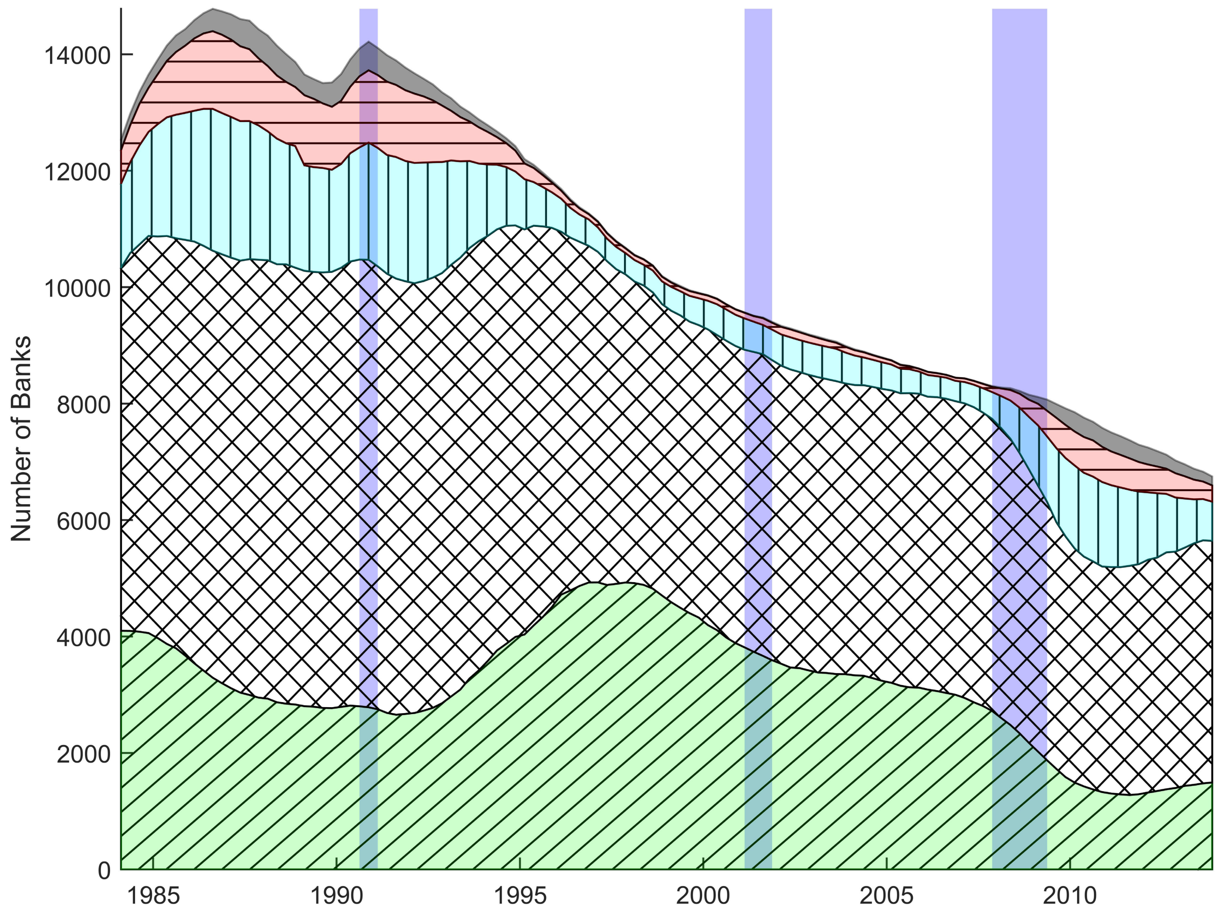

Figure 1: Distribution of CAMELS Ratings 1984-2013: Green, diagonal—1, White, cross-hatched—2, Cyan, vertical—3, pink, horizontal—4, Black—5; Shaded areas—NBER-defined recessions

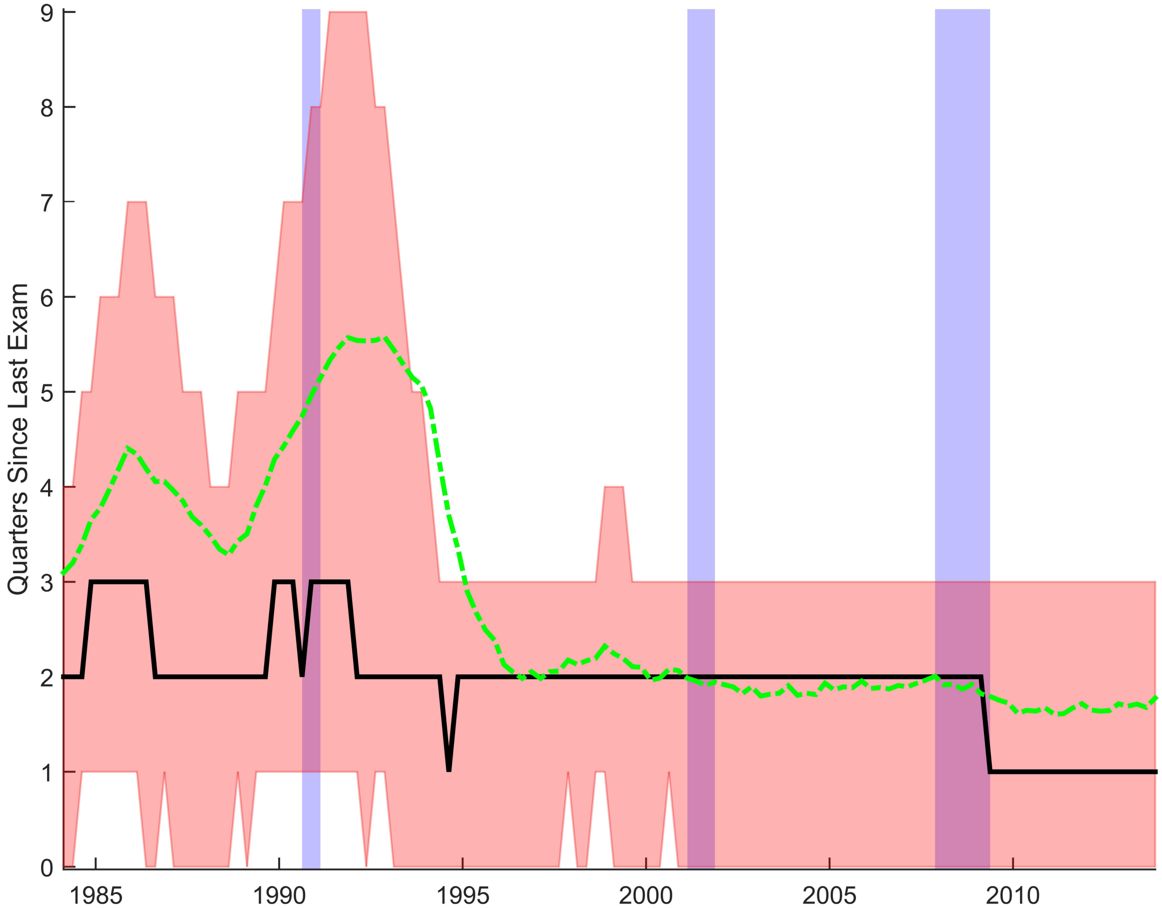

Figure 2: CAMELS exams frequency 1984-2013: Red areas: 25th—75th percentiles; Punctuated green line—mean; Solid black line—median; Blue shaded areas—NBER-defined recessions

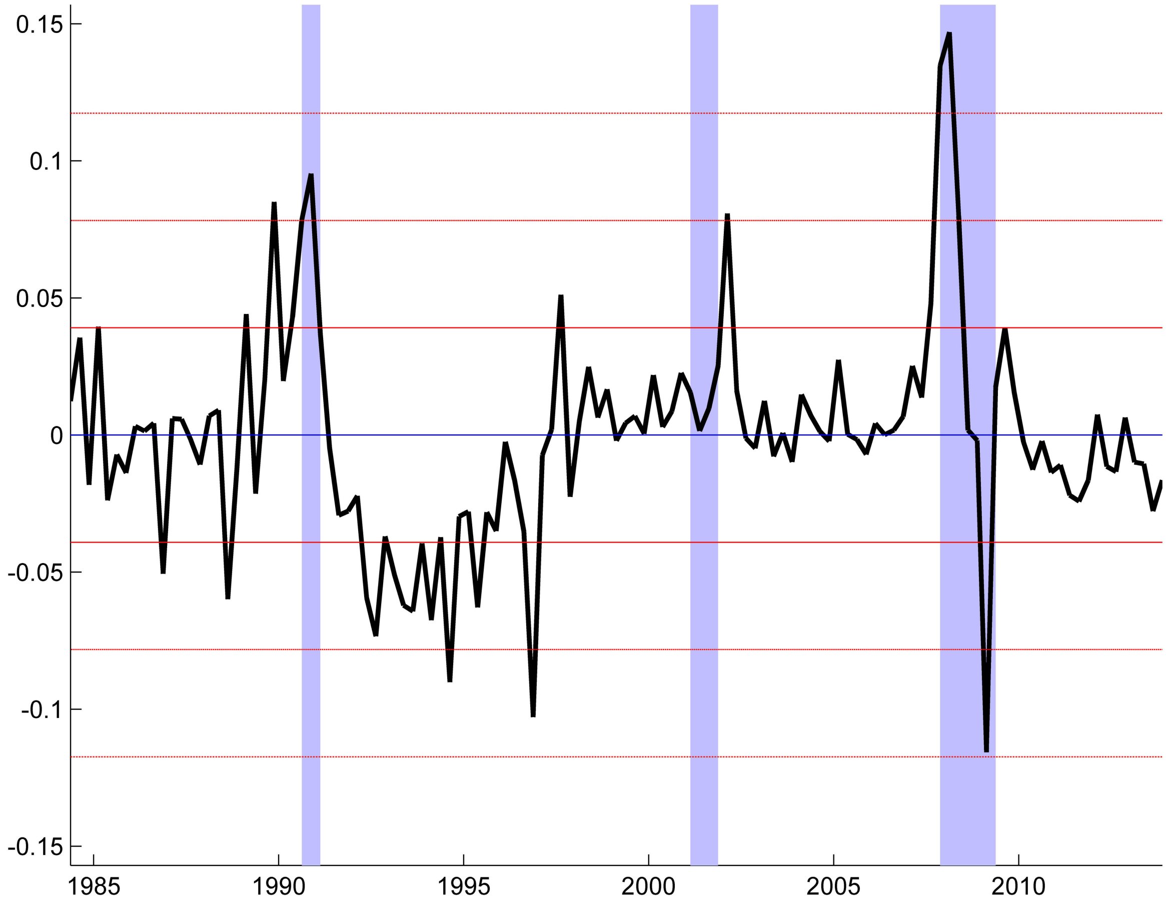

Figure 3: Magnitude of Changes in Asset-weighted Average CAMELS Rating 1984-2013; Shaded areas—NBER-defined recessions; red solid lines: $\pm\sigma_{\triangle r}$; red dashed lines: $\pm 2\sigma_{\triangle r}$; red punctuated lines: $\pm 3\sigma_{\triangle r}$

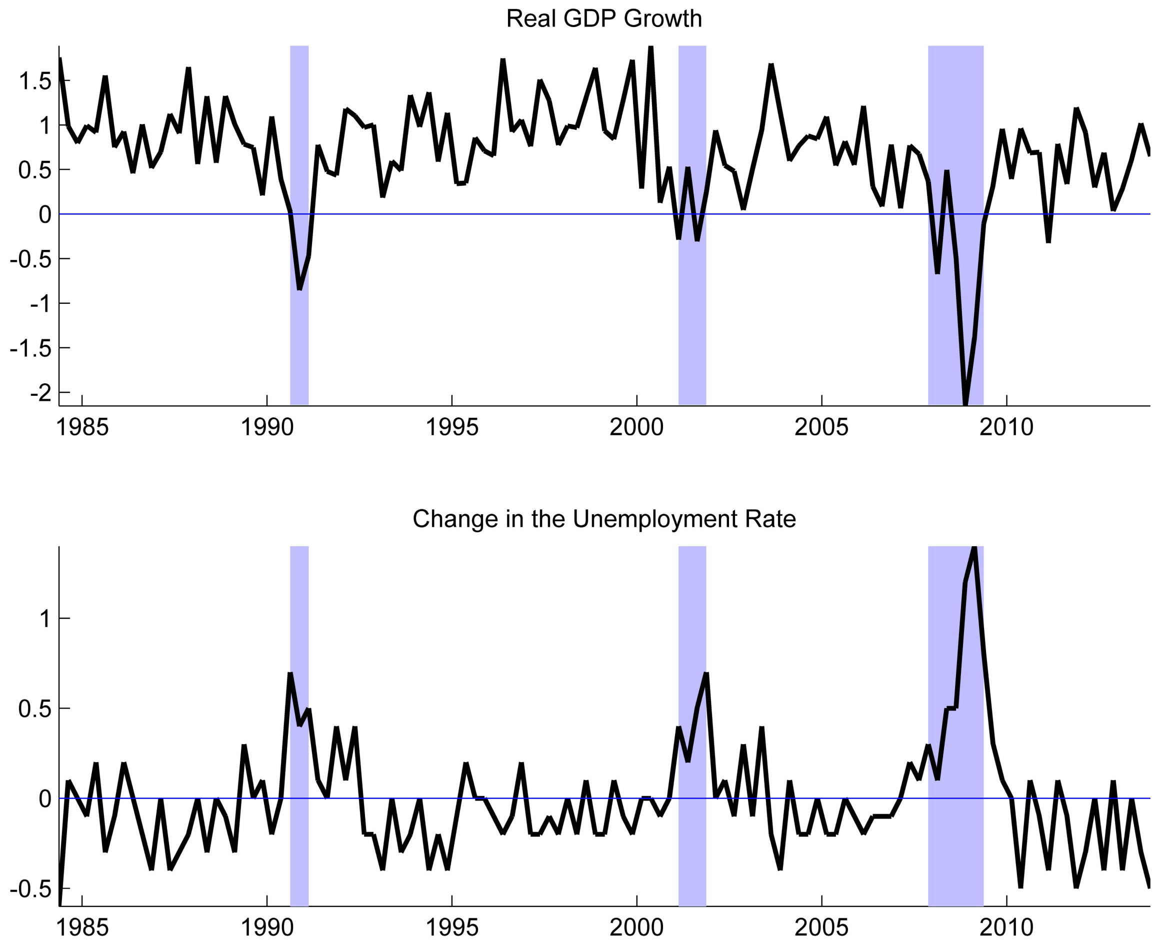

Figure 4: Measures of Real Activity 1984-2013; Shaded areas—NBER-defined recessions

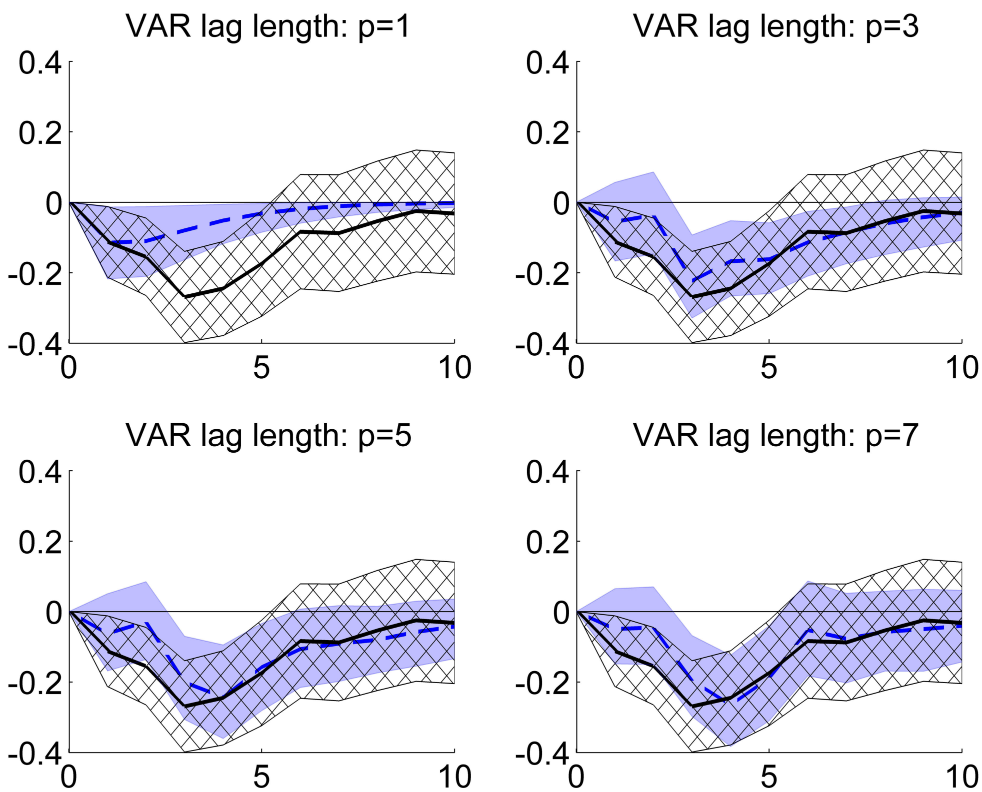

Figure 5: Linear Model IRFs. Real GDP growth as real activity: Filled blue 95% confidence interval and dashed mean response—Cholesky SVAR; Cross-hatched 95% confidence interval and solid mean response—linear local projection; Left column—downgrades; Right column—upgrades

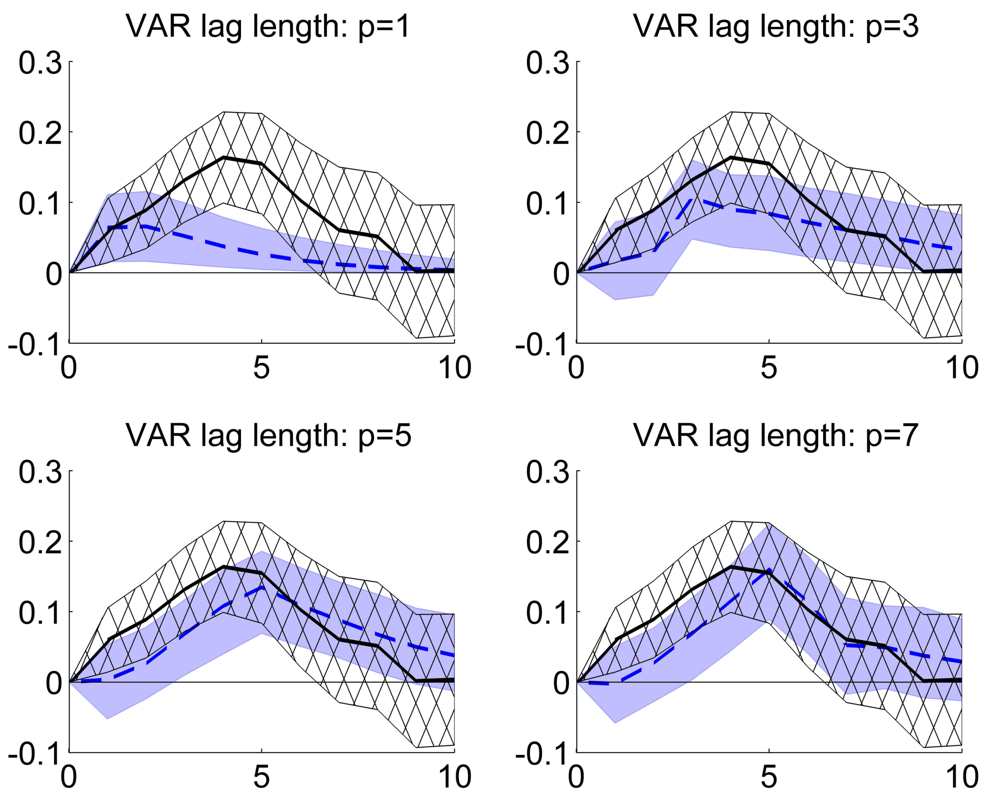

Figure 6: Linear Model IRFs. Change in the Unemployment Rate as real activity: Filled blue 95% confidence interval and dashed mean response—Cholesky SVAR; Cross-hatched 95% confidence interval and solid mean response—linear local projection; Left column—downgrades; Right column—upgrades

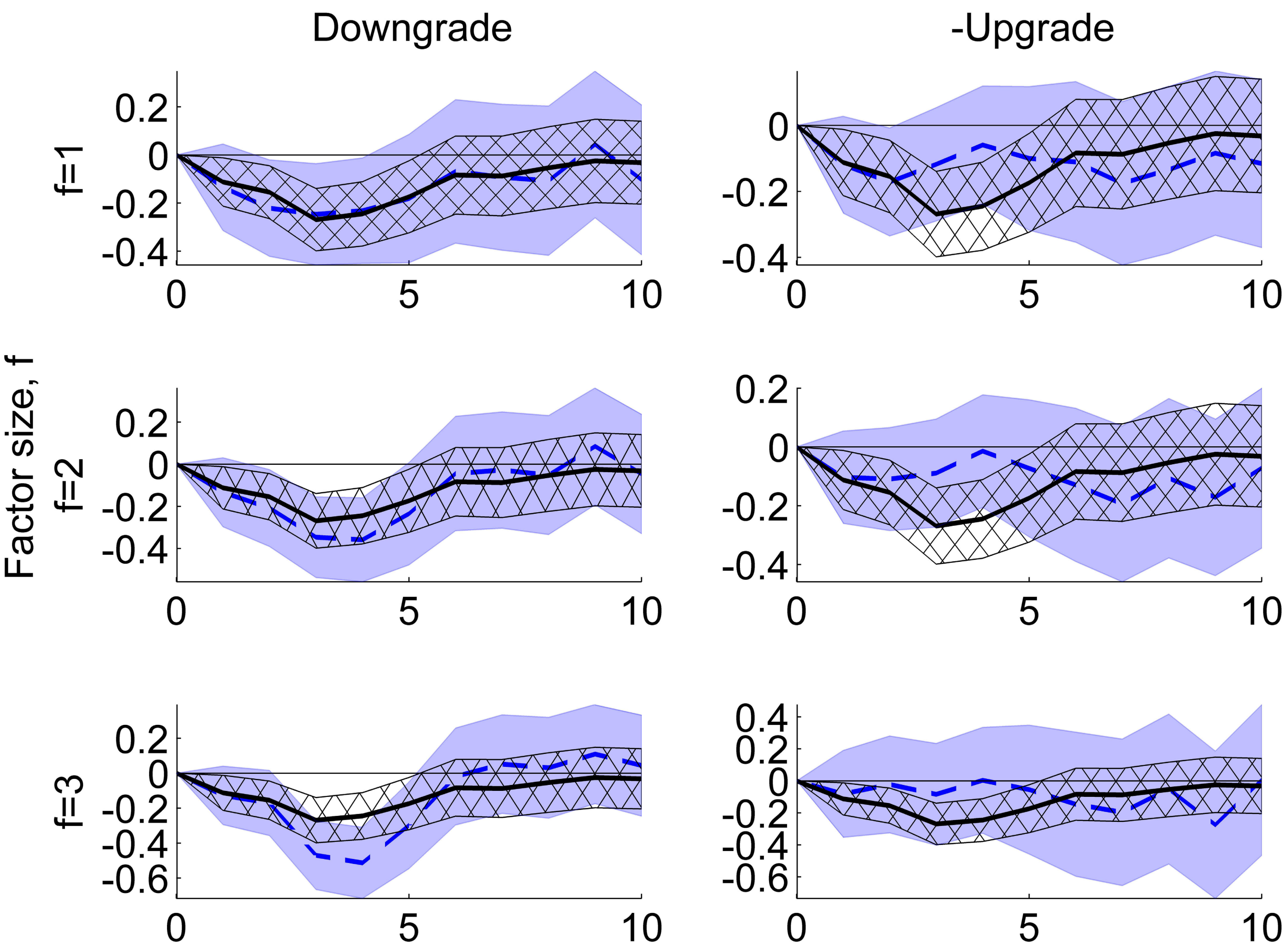

Figure 7: Local Projection IRFs. Real GDP growth as real activity: Filled blue 95% confidence interval and dashed mean response—nonlinear model; Cross-hatched 95% confidence interval and solid mean response—linear model

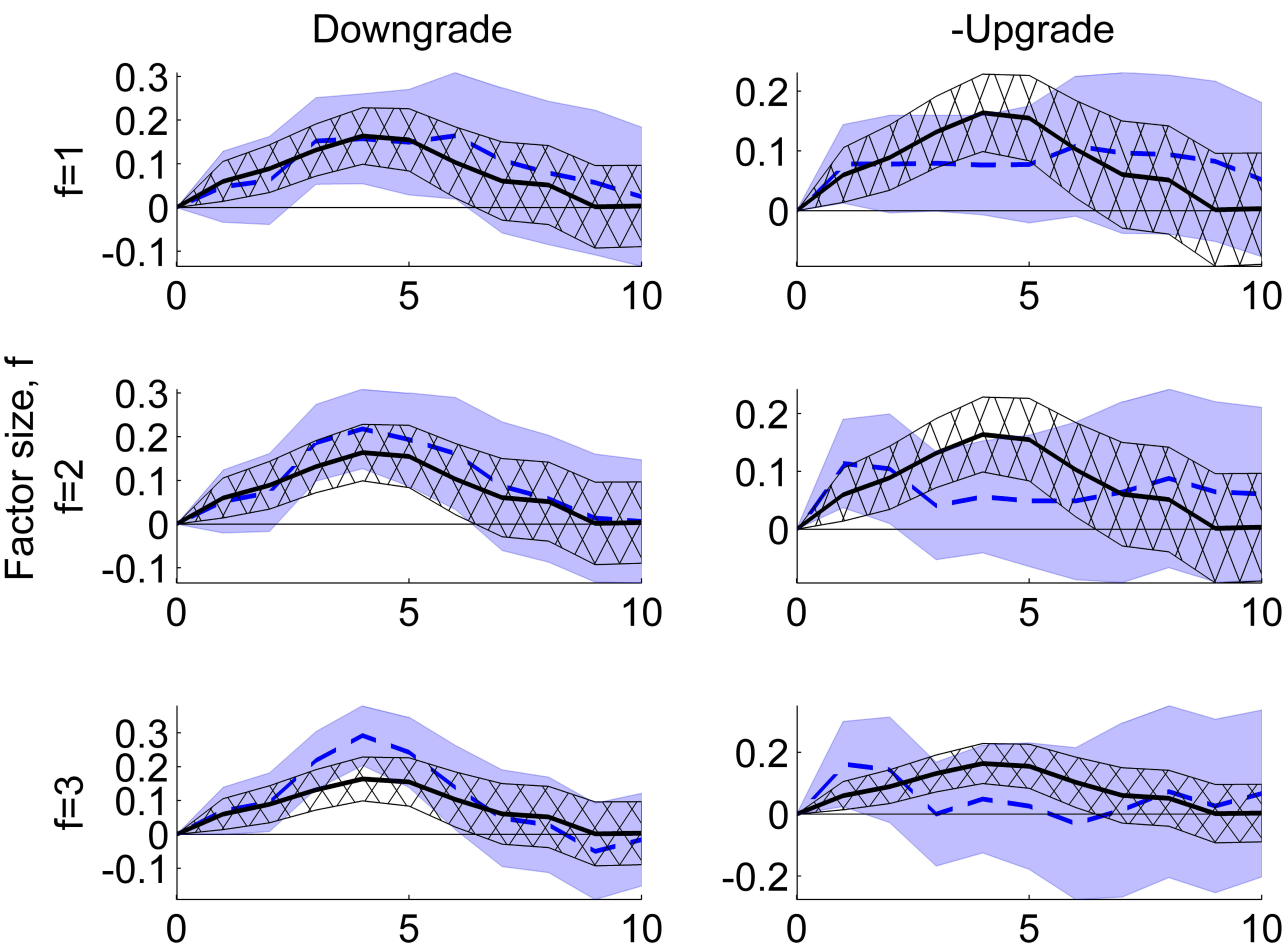

Figure 8: Local Projection IRFs. Change in the Unemployment Rate as real activity: Filled blue 95% confidence interval and dashed mean response—nonlinear model; Cross-hatched 95% confidence interval and solid mean response—linear model

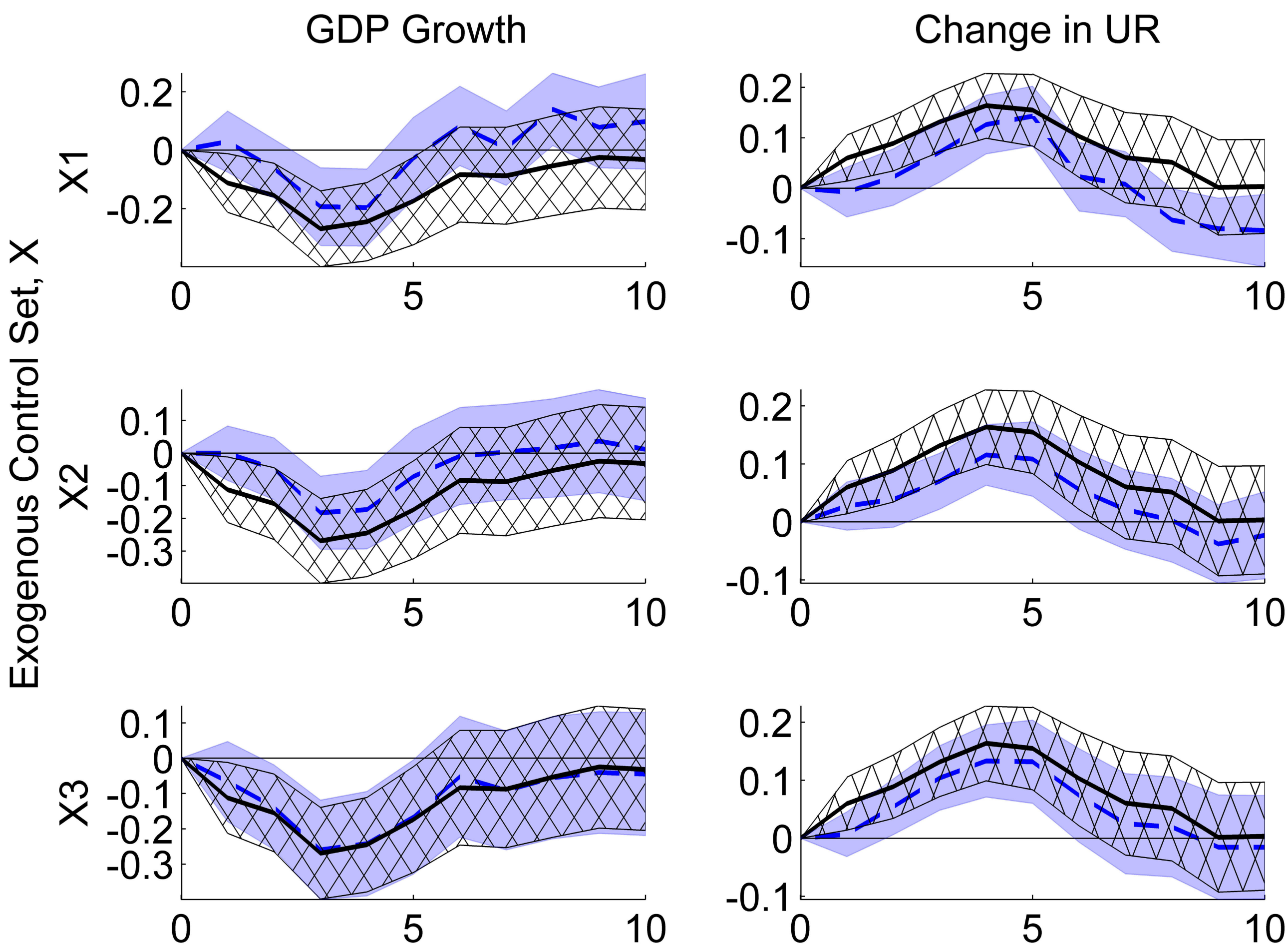

Figure 9: Linear Local Projection IRFs. Left column: Real GDP growth as real activity; Right column: Changes in the Unemployment Rate as real activity. Cross-hatched 95% confidence interval and solid mean response—no exogenous controls; Filled blue 95% confidence interval and dashed mean response—with exogenous controls: X1—current and lagged macroeconomic controls; X2—Banking controls; X3—Survey of Professional Forecasters controls

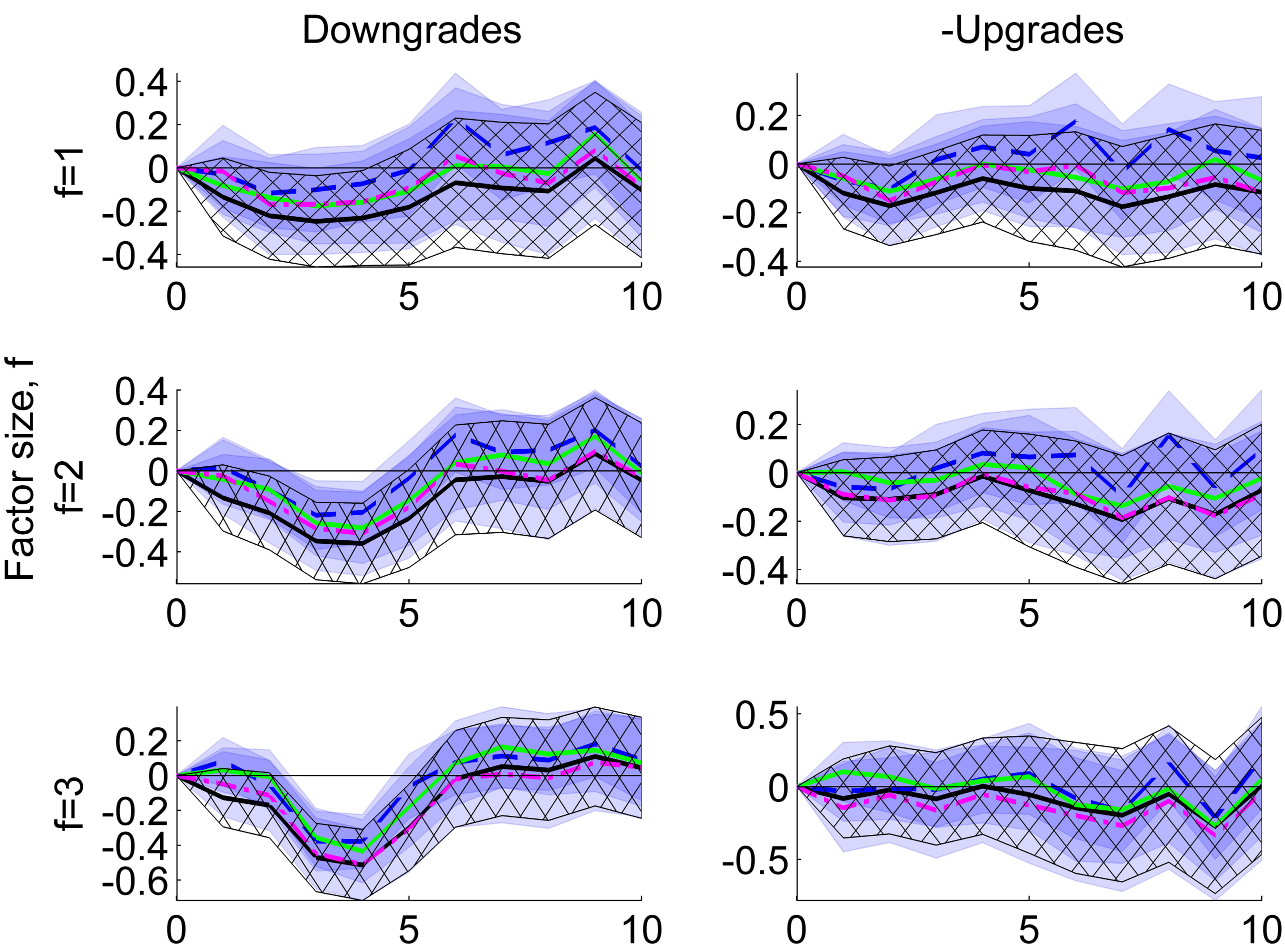

Figure 10: Nonlinear Local Projection IRFs. Real GDP growth as real activity: Cross-hatched 95% confidence interval and solid mean response—no exogenous controls; Filled blue 95% confidence interval—with exogenous controls; Dashed blue line—current and lagged macroeconomic controls (X1); Solid green line—Banking controls (X2); Punctuated magenta line—Survey of Professional Forecasters controls (X3)

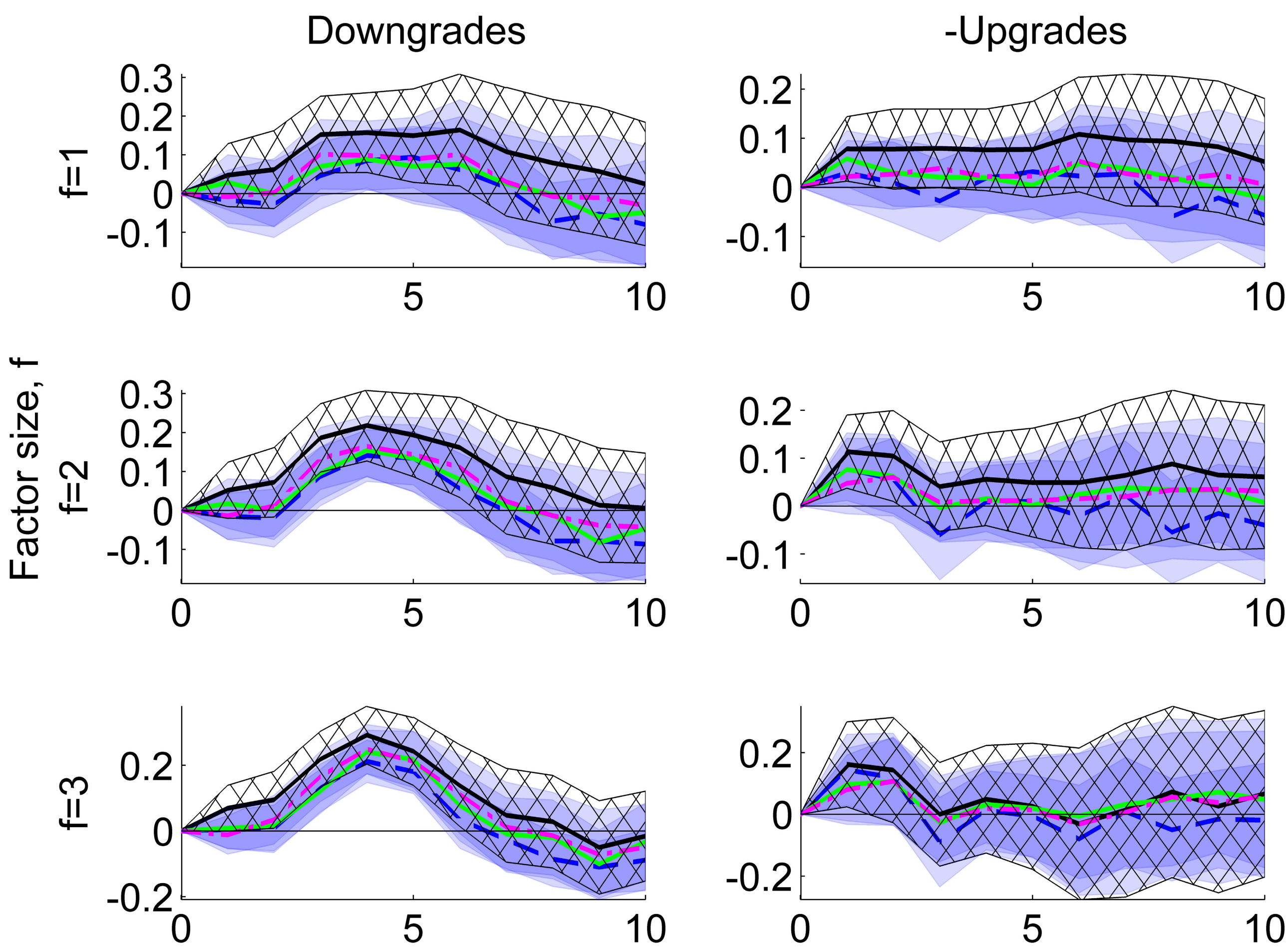

Figure 11: Nonlinear Local Projection IRFs. Change in the Unemployment Rate as real activity: Cross-hatched 95% confidence interval and solid mean response—no exogenous controls; Filled blue 95% confidence interval—with exogenous controls; Dashed blue line—current and lagged macroeconomic controls (X1); Solid green line—Banking controls (X2); Punctuated magenta line—Survey of Professional Forecasters controls (X3)

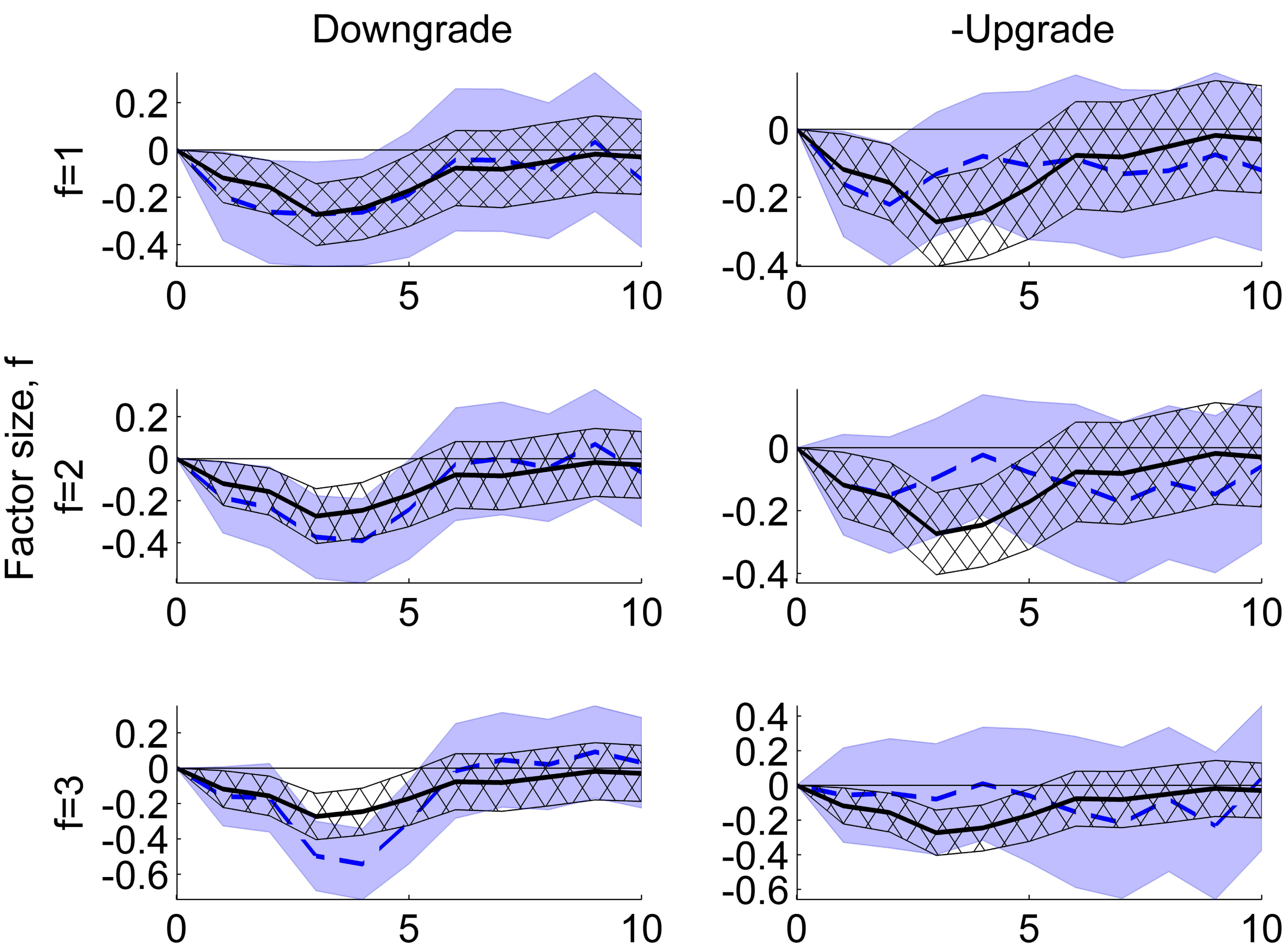

Figure 12: Local Projection IRFs. Five-variable model; real GDP growth as real activity: Filled blue 95% confidence interval and dashed mean response—nonlinear model; Cross-hatched 95% confidence interval and solid mean response—linear model

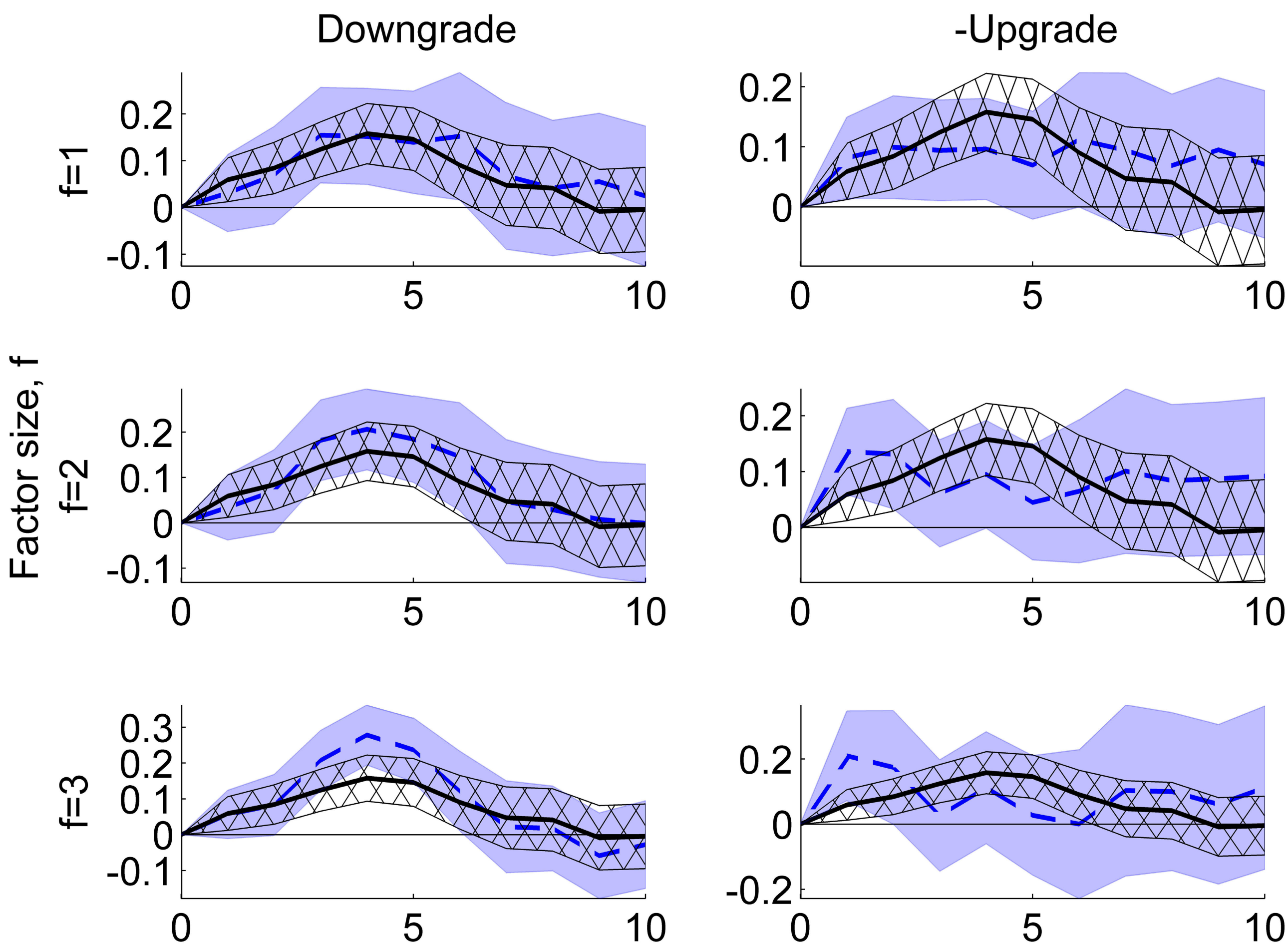

Figure 13: Local Projection IRFs. Five-variable model; change in the Unemployment Rate as real activity: Filled blue 95% confidence interval and dashed mean response—nonlinear model; Cross-hatched 95% confidence interval and solid mean response—linear model