WP/11/26

IMF Working Paper

Reversing the Financial Accelerator: Credit Conditions and Macro-Financial Linkages

Tamim Bayoumi and Reginald Darius

INTERNATIONAL MONETARY FUND

IMF Working Paper

Strategy, Policy, and Review Department

Reversing the Financial Accelerator: Credit Conditions and Macro-Financial Linkages

Prepared by Tamim Bayoumi and Reginald Darius

February 2011

Abstract

This paper examines the role of credit markets in the transmission of U.S. macro-financial shocks through the prism of a financial conditions index (FCI) based on a vector autoregression (VAR) methodology. It explores the relative predictive power of market variables compared to credit standards/conditions. The main conclusion is that under plausible specifications credit conditions dominate market variables, highlighting the importance of credit supply. The fact that direct measures of credit conditions anticipate future movements in asset prices has an extremely important implication. Most models of the credit channel see it as an amplifier of underlying changes in financial wealth. The impact of credit conditions on growth compared to other market variables implies that credit supply drives other financial variables rather than responding to them.

JEL Classification Numbers: E52, E51, E47, E44

Keywords: Output, Financial conditions index, credit conditions

Author's E-Mail Address: tbayoumi@imf.org and rdarius@imf.org

Contents **Page**

I. Introduction and Literature Review

A. Introduction: Turning the Credit Channel on its Head

The 2008 global crisis has refocused interest on macro-financial linkages. The main issue, as so often in economics, is how to model these links in a manner that is both tractable and encompasses the variety of factors involved. One relatively successful way of modeling macro-financial interactions have been Financial Conditions Indices (FCIs). By measuring the impact of changes in financial conditions (such as bond yields, spreads, equity prices as well as short-term interest rates and exchange rates) on real activity, such indices provide a useful metric for assessing the influence of financial conditions on the business cycle.

This paper examines the role of credit markets in the transmission of U.S. macro-financial shocks through the prism of an FCI based on a vector autoregression (VAR) methodology. Earlier work in this area has come up with the striking result that the survey data on bank lending standards from the Fed's Senior Loan Office Survey (SLOS) is an important driver of changes in activity even when asset prices such as equity market valuations and short- and long-term interest rates are included, implying that the availability of bank loans is an important, independent driver of the business cycle with at least as much explanatory power as traditional measures of asset values (Swiston, 2008).

We extend and augment this work in several dimensions. First, we compare the information contained in the SLOS with an alternative measure of credit conditions facing small businesses. This variable measures the tightness of credit conditions from the point of view of borrowers, while the SLOS looks at the same issue from the lender side. The index is part of the wider Small Business Survey (SBS). Small businesses are generally considered an important factor in the transmission of changes in bank credit to the real economy, as they are heavy users of bank loans and, in contrast to larger firms, have less access to bond markets. Second, we investigate the sensitivity of the results to alternative orderings of credit supply variables and financial prices. Finally, we examine the channels through which the supply of credit affects activity.

Anticipating our results, we find that:

- Credit conditions and, in particular, the Fed's Senior Loan Officer's Survey continues to be an important driver of activity under all specifications of the VAR. The small business survey measure is a less important driver of activity, but it matters more if the SLOS is excluded.
- An important reason for the success of the SLOS in the VAR is that it is a useful predictor of subsequent movements in asset prices. Despite this, monetary policy reacts relatively slowly to this measure of future developments.

The fact that direct measures of bank lending conditions anticipate future movements in asset prices has an extremely important implication. While the credit channel involves three interactions—asset prices, banks, and borrowers—most models of this process assume that bank loans are an amplifier of underlying changes in financial wealth. Indeed, this is the basis for the workhorse in the macroeconomic field, the "financial accelerator" model due to Bernanke and Gertler (1995) and Bernanke and Gilchrist (1999). In this model, changes in the value of collateral affect the willingness of banks to lend to entrepreneurs, with a knock-on impact on activity.

Our results, however, turn the causality of the financial accelerator on its head. Instead of changes in the value of wealth driving bank lending, our empirical results imply that in general changes in willingness of banks to lend (often associated with changes in bank capital used to provide a cushion against lending) drive wealth. While this direction of causation has always been clear in banking crises, such as those experienced by the United States and much of western Europe starting in 2007, our results find this to be the usual direction of causation even in more normal times.

Before discussing our approach and results in more detail, it is useful to deal up front with one potential criticism of our results. The idea that information on bank lending conditions can help explain changes in financial prices appears to contradict the efficient markets hypothesis, which says that such prices are unpredictable given existing information. But note that one of the assumptions of the efficient markets hypothesis is that at least some traders have access to virtually unlimited credit in order to arbitrage markets. The Senior Loan Officer's Survey, however, measures the difficulty of obtaining such credit from banks. The fact that changes in the ability to obtain bank credit can drive markets prices with at least some degree of predictability is hence perfectly compatible with the efficient markets hypothesis.

B. Literature Review

The role of asset prices in determining aggregate demand and inflation has been a subject of much interest in the literature and is somewhat contentious. The empirical evidence on the role of asset prices in the transmission mechanism is largely ambiguous and partially at odds with the theoretical perspective, which appears to imply a relatively important role for asset prices. Traditionally the transmission of monetary policy has been explained through either the interest or exchange rate channels. Notable exceptions include Modigliani (1971), which ascribed an important role for property and equity prices through the wealth effect, and Bernanke and Gertler (1989) who argue asset price can also have implications for monetary policy transmission through the credit channel.

The literature on the credit channel of monetary policy examines how changes in the supply of money impact real activity through its effect on the availability of credit. Other studies in this tradition include Bernanke and Blinder (1988), Kashyap and Stein (1994) and Lamont et al (1994). Adrian et al (2009) considers an additional conduit through which monetary policy affect activity "the risk taking channel". In this framework monetary policy action that affects the risk-taking capacity of banks results in shifts in the supply of credit. Meanwhile, Benmelech and Bergman (2009) examine how monetary policy may be rendered ineffective when, despite an infusion of money into the banking system from the central bank, liquidity remains stuck in banks "credit trap".

Empirical studies, which examine the relationship between financial variables and output, suggest that equity returns have limited predictive content for future output. These results are contained in the work, for example, of Fama (1981), Havey (1989), Stock and Watson (1989 and 1999), and Estrella and Miskin (1998).[1] However from a backward looking IS and Phillips curve estimation, Goodhart and Hofmann (2001) find evidence suggesting that equity prices are influential in determining the output gap in G-7 countries. Pichette and Tremblay (2003) finds evidence of weak stock market wealth effect but relatively robust housing price wealth effect for Canada. Zhang (2002) finds that bond risk premium has high predictive power. More recently Gilchrist et el (2009) examined the information content of an array of corporate spreads in predicting economic activity and concluded that credit spreads on senior unsecured corporate debt have substantial predictive power for future economic activity.

Computing the relative impact of financial variables on output has lead to the development of financial conditions indexes (FCIs), which are now commonly used to gauge monetary conditions. FCIs which usually include interest rates, exchange rates, equity and housing market conditions,[2] represents a broadening of the often-used monetary condition index (MCI). The MCI measures financial conditions based on a weighted average of the change in exchange and interest rates. Gauthier et al (2004), Goodhart and Hofmann (2002), and Lack (2002), and Batini and Turnbull (2002) all demonstrate that the predictive power of FCIs in relation to output is relatively robust and the FCI generally outperforms the traditional MCI.

More recently, Swiston (2008) derived a broad base financial conditions indicator (FCI), which in addition to examining price signals of financial markets, sought to also examine the effects of credit supply through bank lending conditions. The FCI model estimated by Swiston (2008) using the VAR framework, includes a wider range of financial variables compared to the popular IS curve base models.[3] Of particular significance is inclusion of a measure of credit availability based on the Federal Reserve's Senior Loan Officers Opinion Survey (SLOS) of

[1] Goodhart and Hofmann (2000) demonstrated that stock prices did not contribute much to predicting inflation.

[2] See for example Romer and Romer (1989), Strongin (1995) and Bernanke and Mihov (1998).

[3] Goodhart and Hofmann (2000, 2001, 2002), Duguay (1994), and Gauthier (2004) includes FCIs estimated using the IS/Phillips curve approach. Goodhart and Hofmann (2001) and Gauthier et al (2004) also derives FCIs based on the VAR approach.

lending conditions. The derived FCI was a good predictor of economic activity, with lending conditions being the most important of the financial variables included in the model.

This paper seeks to explore in more detail the relationship between lending standards and growth, and the dynamic interaction between lending conditions and other financial variables. The paper is related to the work of Swiston (2008) and seeks to establish with greater force the impact of financial variables commonly used in estimating FCIs on output. The paper differs from the majority of papers in the literature in that it jointly examines the impact of financial variables on output growth. This is critical as a number of papers focus on one particular financial variable in determining growth, whereas the interaction of the variables in a joint framework provides an opportunity to distinguish the relative role of different financial variables. In introducing different measures of credit conditions the paper also touches on whether the estimated impact on growth is heavily dependent on the chosen measure of credit supply. In that regard we also experiment with credit conditions for small firms, a sector which is particularly dependent on bank loans as a source of credit. In general by focusing on credit availability the paper provides an empirical assessment of how the "credit trap" may impact on economic activity.

In analyzing the role of credit conditions, specific attention is given to the ordering of variables in the VAR, an issue not specifically addressed in Swiston (2008). Swiston used period averages for all variables, including asset prices, and derived the ordering from assumed sluggishness of the variables relative to each other. We simplify the issues by using end-period data for financial market prices, thus allowing us to order the VAR on the basis of the timing of the data. Since the senior loan officer data (and related small business survey index) refer to behavior during a given quarter, this can be ordered before the end-period asset prices as bank behavior can affect prices but not vice versa. To test for robustness, we also experiment with alternative ordering using period averages, to ensure that our results do not reflect the fact we are taking end-period "snap shots" of asset valuations. Alternative ordering, when credit supply measures ordered after time-averaged market variables indicate a significantly larger role for equity prices (but not other asset prices), but credit conditions retain an important role.

II. Model and Estimation Method

A. The basic model and survey data

The U.S. FCI model we explore follows a Choleski factorization and contains macroeconomic variables, measures of credit supply conditions, policy interest rates, and financial asset prices. More specifically, the VAR has the following ordering of variables: log of real gross domestic product; log of the gross domestic product deflator; measures of bank loan standards (initially the senior loan officer survey sentiment index); the three month LIBOR interest rate (the main private sector short-term borrowing rate, which is driven by changes in monetary policy); log of the real effective exchange rate; the spread of investment grade over high yield corporate bonds; investment grade corporate yield; and log of the real equity prices.[4]

The ordering is based on the following considerations. The macroeconomic variables come first given the relative sluggishness of their responses, using the standard assumption in monetary VARs that real GDP is placed ahead of prices. Next come measures of credit conditions—the SLOS and/or the SBS measure of credit conditions. End period asset prices—LIBOR, equities, bond spreads, and the real effective exchange rate—are placed last. One implication of this ordering is that the credit conditions are put before the LIBOR rate—our proxy for monetary policy. However, it turns out that the ordering between these sets of variables is not unimportant for the results.

With the sample starting in the early 1990s due to the inclusion of the SLOS and SBS (see below), degrees of freedom are an important consideration. Accordingly, a lag length of two was chosen for the VAR based on the Schwatz Bayesian information criteria (Table 1). This criterion makes an adjustment for degrees of freedom, unlike many other tests for lag length (such as the Aikai information criterion or the likelihood ratio test).

Given the importance of measures of credit availability in this paper, it is worth discussing the sources and nature of these data in more detail. The Senior Loan Officer's Survey (SLOS) is a quarterly survey produced by the Federal Reserve Board (Fed). Senior loan officers are asked their views on a series of issues, but the most important for this paper (and most other analysis) is whether their institution is tightening or loosening credit standards compared to the previous quarter for a series of types of loans (to large corporates, small- and medium-sized corporates, commercial real estate, and mortgage lending). The results are generally reported as a sentiment index, where the difference is the percentage of those saying they are tightening standard is subtracted from those who say they are loosening standards (there is also a "no change" option).[5] While there was an earlier survey that was discontinued, the more recent variant is available from1990Q2.[6] It has been used successfully in a number of papers to examine the behavior of banks.[7]

[4] We measure the asset prices as end-period data. More specifically, in the case of the LIBOR, and the REER we use the December value. While in the case of equities high yield spread, corporate yield we use the end period data and derive the real values by deflating by the end December CPI.A more detailed description of the data is available in Annex 1.

[5] The survey itself distinguished between "rapidly" and "slowly" tightening standards, but this is ignored in most analysis.

[6] Survey data on lending standards for consumer loans is available for a much longer period starting prior to 1970. However, the earlier data appear relatively unreliable. In particular, a number of methodological changes have occurred during the period for which the data is available which would raise questions about the underlying properties of the data. The most significant recent adjustment occurred in 1990, when respondent panel was enlarged to include 18 of the largest U.S branches and agencies of foreign banks.

[7] See for example Lown et al (2000) and Lown (2006)

While the SLOS covers standard quarters (i.e. the last one of the year covers October to December), it is published with some lag—generally coming out in early February. There is thus a dissonance between the period the survey covers and the timing at which the data are available. We include the variable over the quarter to which the survey refers, as this is the period over which the change in lending conditions occurs. An interesting feature of the survey is that it may well be a useful forecaster of bank loans, as it may well take time for changes in views about the ease of lending to percolate through to behavior on the ground.

The Small Business Survey (SBS) is a monthly survey of sentiment in small businesses conducted by the National Federation of Independent Business (NFIB) since 1987. The results are compiled relatively fast, with data for (say) December coming out by the first week in January. As with the SLOS, this is reported as a sentiment index (the percentage saying conditions are improving versus worsening). Note that a higher index implies a loosening of standards (the opposite the convention in the SLOS).

B. Role of senior loans survey of credit conditions (SLOS): Baseline model

Our baseline specification confirms the importance of the SLOS in predicting output and the results are relatively independent of whether the credit variable is the small- and medium-sized firm survey rather than the large company (the results we report). Overall, the model explains a respectable percent of the variance of growth suggesting that this approach has some value in predicting the business cycle.

Examining the impulse responses of real GDP, economic activity is relatively sensitive to lending standards, particularly in the longer-term (Figure 1). A one standard deviation shock is associated with a highly-significant 0.3 percent decline in output after one year, rising to 0.4 percent after 2 years. By contrast, the 3-month LIBOR rate has a much more temporary and only marginally significant impact on output. A one-standard deviation shock peaks at 0.15 percent after 3 quarters and has minimal impact after 2 years. Of the other asset prices, the investment grade spread, high-yield spread, and equity prices all build gradually over time, while the real effective exchange rate follows LIBOR in having only a temporary effect.

Variance decomposition finds that the SLOS survey is the main private sector financial indictor explaining changes in output and dominates all other variables over time (Figure 2). The SLOS survey explains around 19, 41, and 47 percent of output variances after 2, 4, and 8 quarters, respectively. For the first 6 months our proxy for monetary policy (the 3-month LIBOR rate) has a larger initial impact which then fades, while collectively other financial asset prices have a surprisingly minor influence (4, 13, and 17 percent). In short, the SLOS seems to be the dominant factor in explaining output fluctuations more than 6 months in the future. (Details of the variance decomposition of growth are reported Appendix Table A1).

III. DOES THE SMALL BUSINESS SURVEY OF CREDIT CONDITIONS (SBS) ADD INFORMATION?

We next examine the relative information content of a more direct—and more timely—measure of credit conditions, namely the measure of credit conditions available to small businesses (SBS) discussed above. Given that SBS is monthly and available before SLOS, the SBS is placed before the SLOS measure. We first examine its value as an addition to the SLOS, then whether it is a useful substitute for the SLOS.

Including SBS before the SLOS series has some impact on the baseline results. The impulse response for the SBS becomes significant after 4 quarters (Figure 3). Parallel to these results, the SBS contribution to the variance decomposition becomes relatively important only after about one year. However, the proportion of output variation accounted for by SLOS is largely independent of the inclusion of SBS (Figure 4), and the SBS becomes almost totally insignificant if placed after the SLOS series. Rather, the main impact of including the SBS is to modestly lower the significance and importance of the asset prices. (Details of the growth variance decomposition is reported Appendix Table A2). All in all, the SBS adds little if the SLOS is also included in the model.

When the SBS measure of credit conditions is included without the senior loan officers survey it is statistically significant but explains only a small proportion of output variance. The impulse response functions indicate that one standard deviation shock to the SBS has a significant impact on output that rises steadily over time (Figure 5). Investment grade and high yield corporate spreads also become much more significant but, intriguingly, the 3-month LIBOR rate becomes marginally less significant. In other words, the strong short-term impact of monetary policy in the baseline VAR appears to depend on the inclusion of the SLOS in the regression. Variance decomposition indicates that SBS has a much reduced impact compared to the SLOS, with the impact from the high yield spread and the investment grade corporate yield rising in importance, while the impact of the LIBOR rate falls (Figure 6).[8]

We next excluded both credit variables from the VAR to see if private asset prices provide substitute for our measures of credit conditions. The answer seems to be that investment grade corporate yield and the SBS measure of credit conditions can reasonably substitute for each other but that the overall fit of the model deteriorates significantly (measured using the R-bar squared of the real GDP equation). When credit variables are excluded entirely, this variable becomes much more important, particularly the contribution to variance decomposition and to a slightly lesser extent in terms of the significance of the impulse response function on output after

---

[8] There are two obvious reasons why the SLOS might be a better measure of credit conditions than the SBS. First, it may take time for the views in head quarters to percolate to lending on the ground, so that changes in the views of senior loan officers lead actual lending conditions as experienced by businesses. In addition, senior loan officers may have a better overview of overall lending condition than business owners, so the survey may better capture actual credit conditions.

2 years. (A similar effect happens to the SBS if the investment grade yield is excluded). However, monetary policy remains ineffectual. In summary, both corporate yields and SBS credit condition seem to be important (and somewhat substitutable) channels through which financial conditions impact output. However it is clear that the SLOS remains important even if the investment grade spread is included. In light of these results in the remainder of this analysis our benchmark model will include only SLOS as the credit variable.

IV. Timing and Ordering of Credit Variables

To this point the credit variables have been ordered before asset prices in the VAR based on the fact that asset prices are end period data. There are possible reasons to object to this ordering on the basis that the evolution of asset prices over the quarter could also matter for economic activity—in other words, that changes in the SLOS only matter because contemporaneous movement in asset prices are excluded. To test for this, we converted the asset prices to period averages and then experimented with VARs placing them both after and ahead of the SLOS. Placing them after the SLOS survey is a test of whether we are losing significant amounts of information from using end-period rather than period-average financial prices. Placing them before goes one step further, and assumes that the behavior of senior loan officers is driven by asset prices rather than asset prices reflecting changes in bank lending conditions. While this seems unlikely—the senior loan officers survey is a relatively slow-moving series and hence would seem most logically to come before asset prices in the VAR—it is a useful robustness check.

Results when period-average asset price data are substituted for end-period data with no changes in the ordering reaffirm the importance of credit conditions in driving the business cycle. The impulse response function shows that the impact on output is similar to the baseline model, while the variance decomposition suggests that the SLOS contribution to the variation in output is even stronger (Figures 7 and 8). (Details of the growth variance decompositions are reported Appendix Table A3).

Placing period-average asset prices before measures of credit, causes a notable change in the relative importance of the financial channels in explaining output fluctuations. As can be seen in the IRFs reported in Figure 9, the equity price and the investment grade yield become more significant variables, while the impact of shocks to the SLOS remains relatively unchanged compared to the baseline ordering (the impact of money policy shocks is even lower under this ordering).[9] This change in importance can be seen in the variance decomposition, which suggests that under this ordering the investment grade yield and credit conditions are about equally important in explaining output fluctuations after eight quarters, while equity prices

[9] We also experimented with placing the credit variables after the macroeconomic variables and found that the results were basically unchanged from that obtained in the baseline model.

account for the largest share of output fluctuations (Figure 10 and Table A3). The contribution of monetary policy to output variation is notably influenced by the change in the ordering of the credit variables, with the impact been close to zero when credit variables are ordered last (Figure 10).[10] An important observation from this experiment, however, is that even if the credit variable is placed last in the ordering the SLOS measure of credit availability remains highly significant and explains about one quarter of output fluctuations two years out.

V. WHY DOES CREDIT MATTER SO MUCH AND WHAT DOES IT IMPLY?

This section analyzes the channels through which the SLOS affects output in the baseline specification, including its relationship with other financial variables. The dynamic interaction with market variables appears particularly important given that the inclusion of credit supply measures reduces the impact of corporate spreads and adds to the potency of monetary policy in the baseline model. Credit explains about 30 percent of the variation in the policy rate, after one year, and increased to over 50 percent after a couple of years (Figure 11). (See also Appendix Table A4).

Turning to private sector asset prices, a shock to credit has a particularly strong and relatively fast impact on high yield spreads, which gradually declines overtime (Figure 12). Similarly, the impact on corporate yield rises over the first three quarters and then diminishes towards the end of the forecast period. The impact on equity price, by contrast, is sluggish- and highly persistent. The interesting point here is that the impact on corporate yield and high yield spread dies off whilst that on equity prices and policy rates is quite persistent. (See also Appendix Table A5).

Credit condition measured by SLOS explains a significant proportion of the variation in financial market prices. Credit conditions explain above 40 percent of the variation in high yield spread from four quarters onwards, and about 20 percent of the variation in equity prices after 4 quarters rising to about 40 percent after 8 quarters. By contrast, policy rate and the exchange change accounts for most of the variation in corporate yield, with credit variables explaining less than 5 percent of the fluctuation throughout the forecast horizon.

The counter to the above analysis is an examination of the impact of financial shocks on credit conditions (Figure 13). Shocks to policy and the exchange rates have the strongest impact on SLOS, a response that is rather sluggish but highly persistent, while the impact of high yield spreads is shorter, peaking at about 2 or 3 quarters.

---

[10] The core model was also estimated with the senior loans officers lending standards for consumer loans. However this variable generated weaker credit effects on output and surprising on private consumption. In fact the effect of the small business measure on consumption was greater. Given these results and the accompanying weaknesses in this survey measure noted in footnote 7, the other credit measures were deemed preferable.

On a more general level, the fact that credit conditions explain a significant proportion of the variation in other financial variables and the policy variable suggest that it is indeed central to understanding the transmission of financial shocks to the real economy. This result is reinforced by the fact that financial variables explain little of the variation in credit condition. This suggests that the information content of credit variables encompasses much of what is contained in the other financial variables in the model.

The intuition behind the impact of credit conditions on asset price is relatively straightforward. Improve credit conditions drives greater availability of credit and implies reductions in spreads. To the extent that asset prices are driven by the availability of credit as demonstrated by the above results provides empirical validity to the central hypothesis of this paper that there exists a direct credit channel. The converse of which is that if the banks restrict credit this is likely to have a very direct effect on asset prices and growth.

VI. Conclusions

This paper has investigated the role of credit conditions in explaining output and in particular compares the impact effect and the forecasting properties of alternative measures of credit supply. The paper also examines the relative predictive power of other market variables relative to that of credit standards/conditions. The main conclusion is that credit conditions provides an important conduit through which financial conditions affect real output, with credit supply being the dominant influence in most specifications. The impact of credit conditions on growth compared to other market variables reflects in part the fact that credit supply has a significant impact on financial prices.

The literature on transmission of the shocks from the financial sector to the real economy tends to emphasize the indirect credit channel through balance sheet effects. The traditional financial accelerator mechanism emphasizes that changes in wealth through market conditions affect output directly, with the credit channel and the financial accelerator as an amplification mechanism. By contrast, the results in this paper suggest that credit availability has a direct impact on output.

The result from this study and others suggest that credit conditions should be at the core of any analysis of the business cycle. Fortunately, in deriving FCI's, a number of studies now explicitly include measures of lending standards in addition to various market variables. Furthermore in cases where central banks explicitly calculate FCIs, such as Canada, credit conditions are now included in the core framework. Unfortunately, in many cases survey data on credit availability is not available or the data available for only a few years, which limits the extent to which credit conditions can be formally incorporated in empirical studies.

References

Adian, T., E. Moench and H. Shin, 2009, Macro Risk Premium and Intermediary Balance Sheet Quantities. Paper presented at the 10th Jacques Polak Annual Research Conference, IMF Washington DC-November 5-6, 2009.

Batini, N., and K. Turnbull, 2002, "A Dynamic Monetary Conditions Index for the UK," Journal of Policy Modelling, Vol. 24 (June), pp. 257–81.

Bayoumi, T., and O. Melander, 2008, "Credit Matters: Empirical Evidence on U.S. Macro-Financial Linkages," forthcoming IMF Working Paper.

Beaton, K., R. Lalonde, and C. Luu 2009, " A financial Conditions Index for the United States," Bank of Canada Working Paper 2009-11.

Benmelech, E., and N. Bergman, 2009, Credit Traps. Paper presented at the 10th Jacques Polak Annual Research Conference, IMF Washington DC-November 5-6, 2009.

Bernanke, B. and M. Gertler. 1989. "Agency Costs, Collateral and Business Fluctuations." American Economic Review 79: 14–31.

Bernanke, B., and A. Blinder, 1988, "Credit, Money, and Aggregate Demand," American Economic Review, Vol. 78 (May: Papers and Proceedings), pp. 435–9.

———, 1992, "The Federal Funds Rate and the Channels of Monetary Transmission," American Economic Review, Vol. 82 (September), pp. 901–921.

———, Gertler, M., 1995, "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," Journal of Economic Perspectives, Vol. 9 (Fall), pp. 27–48.

———, Gilchrist, S., 1999, "The Financial Accelerator in a Quantitative Business Cycle Framework," in J. Taylor & M. Woodford (eds.), Handbook of Macroeconomics, Vol. 1C, pp. 1341–1393.

———, Mihov, I., 1998, "Measuring Monetary Policy," Quarterly Journal of Economics, Vol. 113 (August), pp. 869–902.

Christiano, L., M. Eichenbaum, and C. Evans, 1996, "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," The Review of Economics and Statistics, Vol. 78 (February), pp. 16–34.

Duguay, P. 1994. “Empirical Evidence on the Strength of the Monetary Transmission Mechanism in Canada.” Journal of Monetary Economics 33: 39–61.

Eika, K.H., N.R. Ericsson, and R. Naymoen. 1996. “Hazards in Implementing a Monetary Conditions Index.” Oxford Bulletin of Economics and Statistics 58(4): 765–90.

Estrella, A. and F.S. Mishkin. 1998. “Predicting U.S. Recessions: Financial Variables as Leading Indicators.” Review of Economics and Statistics 80: 45–61.

Fama, E.F. 1981. “Stock Returns, Real Activity, Inflation and Money.” American Economic Review 71: 545–65.

Gauthier, C., C. Graham, and Y. Liu, 2004, “Financial Conditions Indexes for Canada,” Bank of Canada Working Paper 2004-22.

Gilchrist, S., V. Yankov and E. Zakrajsek 2009, Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets, Journal of Monetary Economics, Vol. 56 pp 471-493.

Goodhart, C., and B. Hofmann, 2001, “Asset Prices, Financial Conditions, and the Transmission of Monetary Policy,” Paper presented at conference on Asset Prices, Exchange Rates, and Monetary Policy. Available online at: http://www.frbsf.org/economics/conferences/0103/index.html

———, 2002, “Asset Prices and the Conduct of Monetary Policy,” Paper presented at Royal Economic Society Annual Conference.

Goodhart, C. and B. Hofmann. 2000. “Financial Variables and the Conduct of Monetary Policy.”Sveriges Riksbank Working Paper No. 112.

———, 2006, “The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey,” Journal of Money, Credit, and Banking, Vol. 38 (September), pp. 1575–97.

Kashyap, A., and J. Stein, 1994, Monetary Policy and Bank Lending in N. Gregory Mankiw (ed). Monetary Policy, University of Chicago Press.

Harvey, C.R. 1989. “Forecasts of Economic Growth from the Bond and Stock Markets.” Financial Analyst Journal 45(5): 38–45.

Lack, C. 2002. “A Financial Conditions Index for Switzerland,” Paper prepared for the BIS

Autumn Central Bank Economist Meeting of 14-15 October 2002,. Macroeconomic Advisers. 1998. “From the U.S. Economic Outlook.” Technical Notes: September 5.

Lamont, O., and J. Stein, 2006. “Investor Sentiment and Corporate Finance: Micro and Macro,” American Economic Review Papers and Proceedings, 96, 147-151.

Lown, C., D. Morgan, and S. Rohatgi, 2000, “Listening to Loan Officers: The Impact of Commercial Credit Standards on Lending and Output,” Federal Reserve Bank of New York Economic Policy Review (July), pp. 1–16.

Lown, C. and D. Morgan, 2006, “The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey,” Journal of Money, Credit and Banking, Vol. 38, No. 6, pp. 1575–1597

Modigliani, F. 1971. “Monetary Policy and Consumption.” In Consumer Spending and Monetary Policy: The Linkages. Federal Reserve Bank of Boston.

Pichette, L. and D. Tremblay. 2003. “Are Wealth Effects Important for Canada?” Bank of Canada Working Paper No. 2003-30. 28

Ravn, M.O. and H. Uhlig 2002. “Notes on Adjusting the Hodrick-Prescott Filter for the Frequency of Observations.” The Review of Economics and Statistics 84(2): 371–80.

Rigobon R., (2003). “Identification Through Heteroskedasticity”, Review of Economics and Statistics, vol. 85, issue 4.

Romer, C., and D. Romer, 1989, “Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz,” in O. Blanchard and S. Fischer (eds.), NBER Macroeconomics Annual (Cambridge, MA: MIT), pp. 121–70.

Stock, J.H. and M.W. Watson. 1989. “New Indexes of Coincident and Leading Economic Indicators.” In Macroeconomic Annual, edited by O.J. Blanchard and S. Fischer, 352–94. NBER.

Strongin, s., 1995, “ The Identification of Monetary Policy Disturbances: Explaining the Liquidity Puzzle,'' Journal of Monetary Economics, Vol. 35 (August), pp. 463-97.

Swiston, A. 2008. A US Financial Conditions Index: Putting Credit Where Credit is Due, IMF Working Paper, 08/161.

———. 1999. “Forecasting Inflation.” Journal of Monetary Economics 44: 293–335.

———. 2000. “Forecasting Output and Inflation: The Role of Asset Prices.” Paper presented at the Sverriges Riksbank and Stockholm School of Economics Conference on Asset Market and Monetary Policy, Stockholm, June.

Zhang, Z. 2002. “Corporate Bond Spreads and the Business Cycle.” Bank of Canada Working Paper No. 2002-15.

Data Appendix

Corporate yield is a weighted average of yield on all BBB-A and all AA-AAA 5 to 10 year corporate bonds

Equity price is captured by the Stock Price Index: Standard & Poor's 500 Composite

High yield spread is difference between the weighted average of the yield on all BB, B 5 and C 5 to 10 year corporate bonds and our measure of investment grade corporate yield defined above.

Output is measured by real chained link GDP

The oil price is the spot oil price (West Texas Intermediate ($/Barrel)) deflated by US GDP deflator.

The policy rate is taken as the 3-month London Interbank Offer Rate: Based on US$ (%)

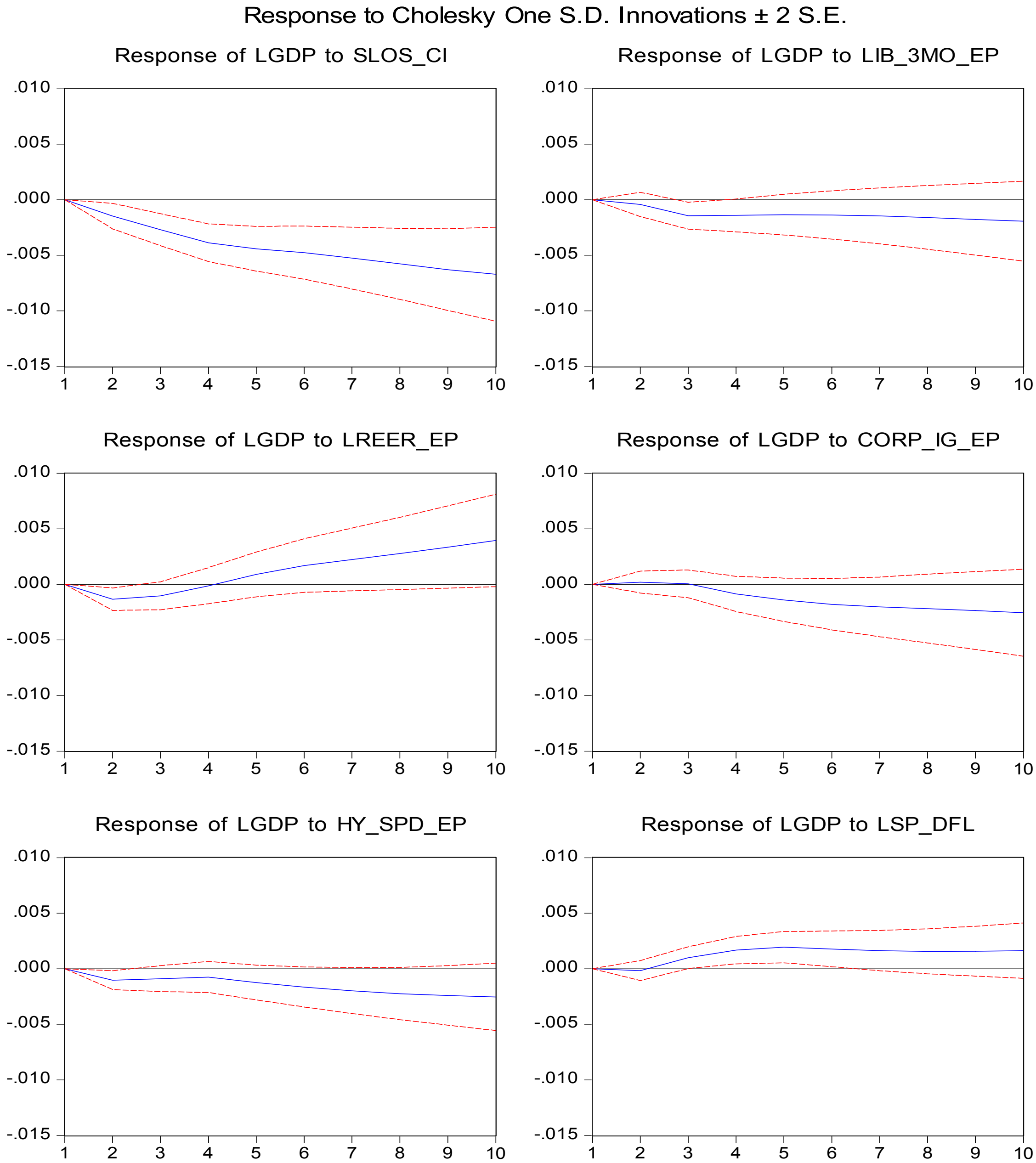
The exchange rate measure is based on the real broad trade-weighted exchange value of the US$ (Mar-73=100)

Table 1: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
	Model 1					
0	-365.9	NA	0.0	9.5	9.8	9.6
1	607.7	1675.9	0.0	-12.6	-9.3*	-11.2*
2	746.6	204.0	6.80e-19*	-13.6	-7.3	-11.1
3	851.3	127.2	0.0	-13.7	-4.4	-10.0
4	980.7	124.5*	0.0	-14.4*	-2.2	-9.5
	Model 2					
0	-190.3	NA	0.0	5.4	5.7	5.5
1	696.7	1534.2	0.0	-16.4	-13.5*	-15.3
2	819.0	181.9	2.22e-19*	-17.5	-12.2	-15.3*
3	904.0	105.5*	0.0	-17.6	-9.8	-14.5
4	1003.0	99.1	0.0	-18.1*	-7.7	-14.0
	Model 3					
0	-29.0	NA	0.0	1.0	1.3	1.1
1	842.8	1508.0	0.0	-20.3	-17.5*	-19.2
2	940.7	145.6	0.0	-20.8	-15.5	-18.7
3	1025.9	105.8	0.0	-20.9	-13.1	-17.8
4	1138.8	113.0	0.0	-21.8	-11.4	-17.6
	Model 4					
0	56.8	NA	0.0	-1.3	-1.0	-1.2
1	955.0	1586.4	0.0	-22.9	-20.7*	-22.0*
2	1037.3	128.3	0.0	-23.4	-19.3	-21.8
3	1102.4	87.9	0.0	-23.4	-17.4	-21.0
4	1176.0	84.1	0.0	-23.7	-15.7	-20.5

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Figure 1. Response of GDP to financial variables including SLOS [11]



---

[11] In what follows LGDP is the log of GDP, LIB_3MO is the three month LBOR, LREER is the log of the real effective exchange rate, HY_SPD is high yield spread, LSP_DFL is the log of real equity price measured by the S&P 500 index, CORP_IG is the corporate yield on investment grade bonds, SLOS_SF is the senior loans officers survey of small firms, SBS_CCE is the small business survey of whether credit conditions are expected to ease by the National Federation of Independent business. End period variables ends with _EP with the exception of LSP_DFL which denotes end period.

Figure 2. VDC Baseline Model

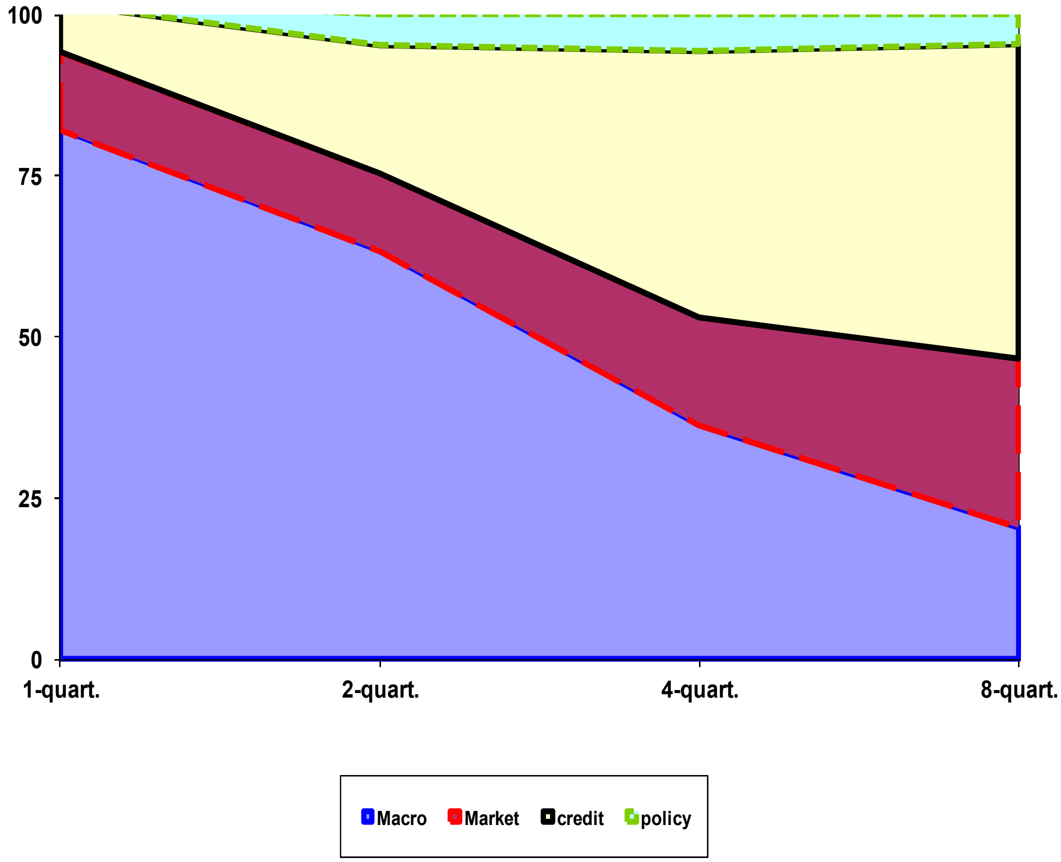


Figure 3. Response of GDP to financial variables including SLOS and SBS

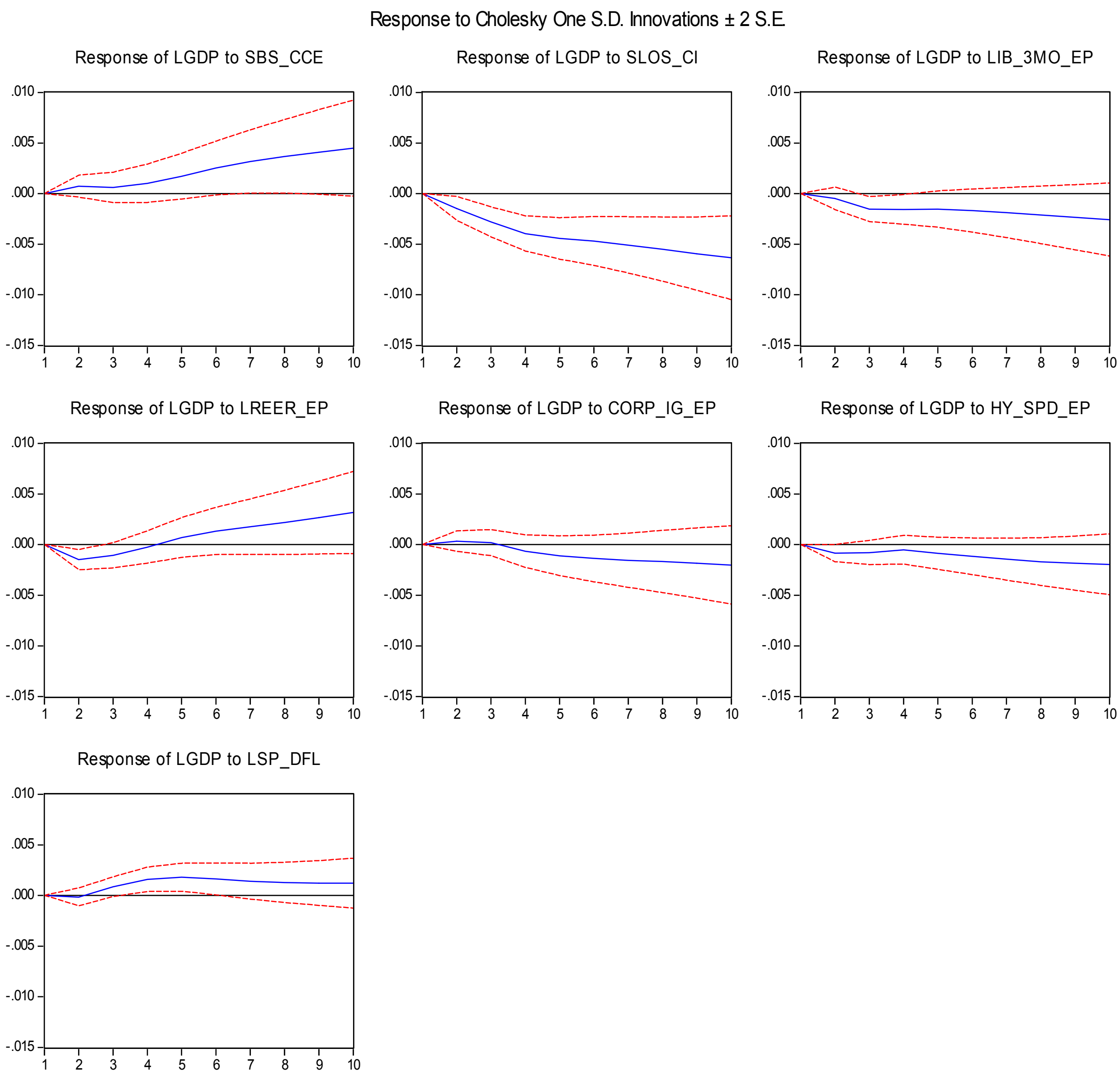


Figure 4. VDC of GDP in model including SLOS and SBS

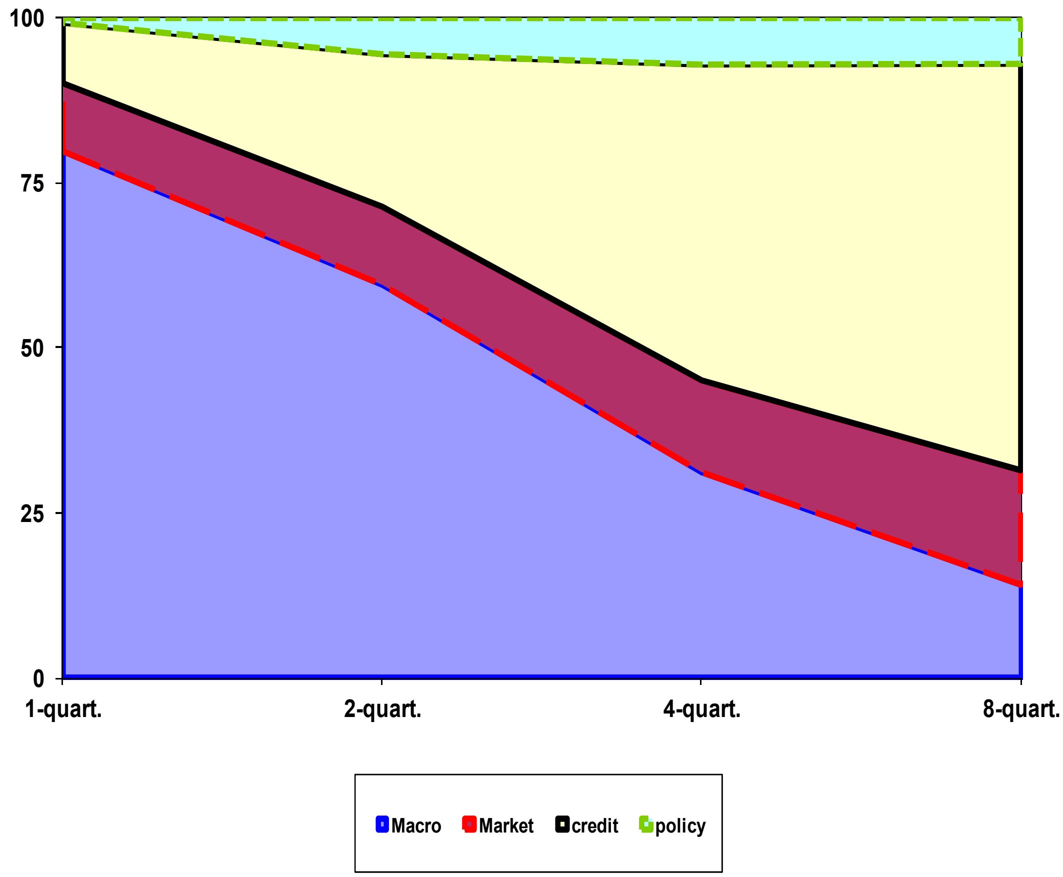


Figure 5. Response of GDP to financial variables in model with SBS

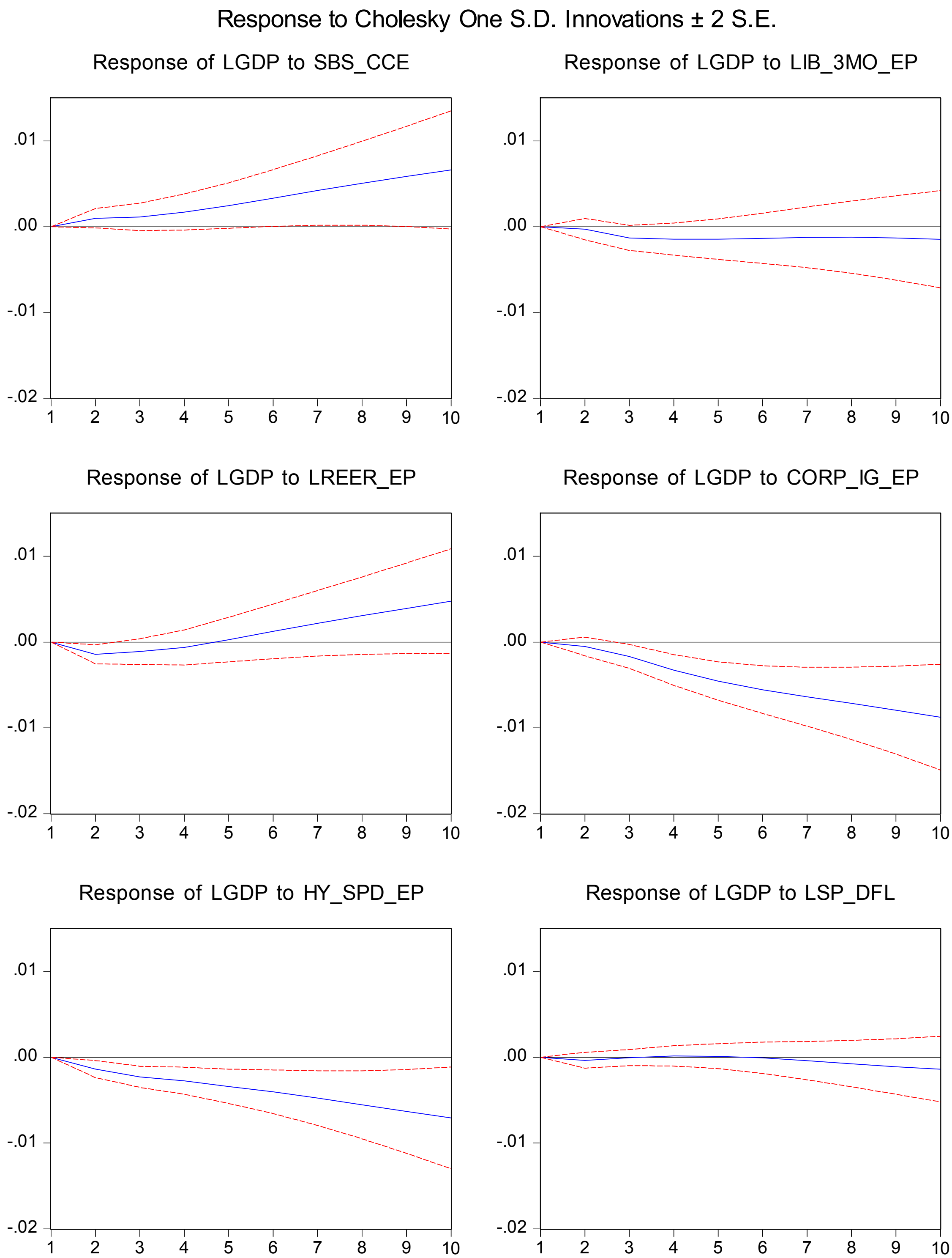


Figure 6. VDC of GDP in model with only SBS

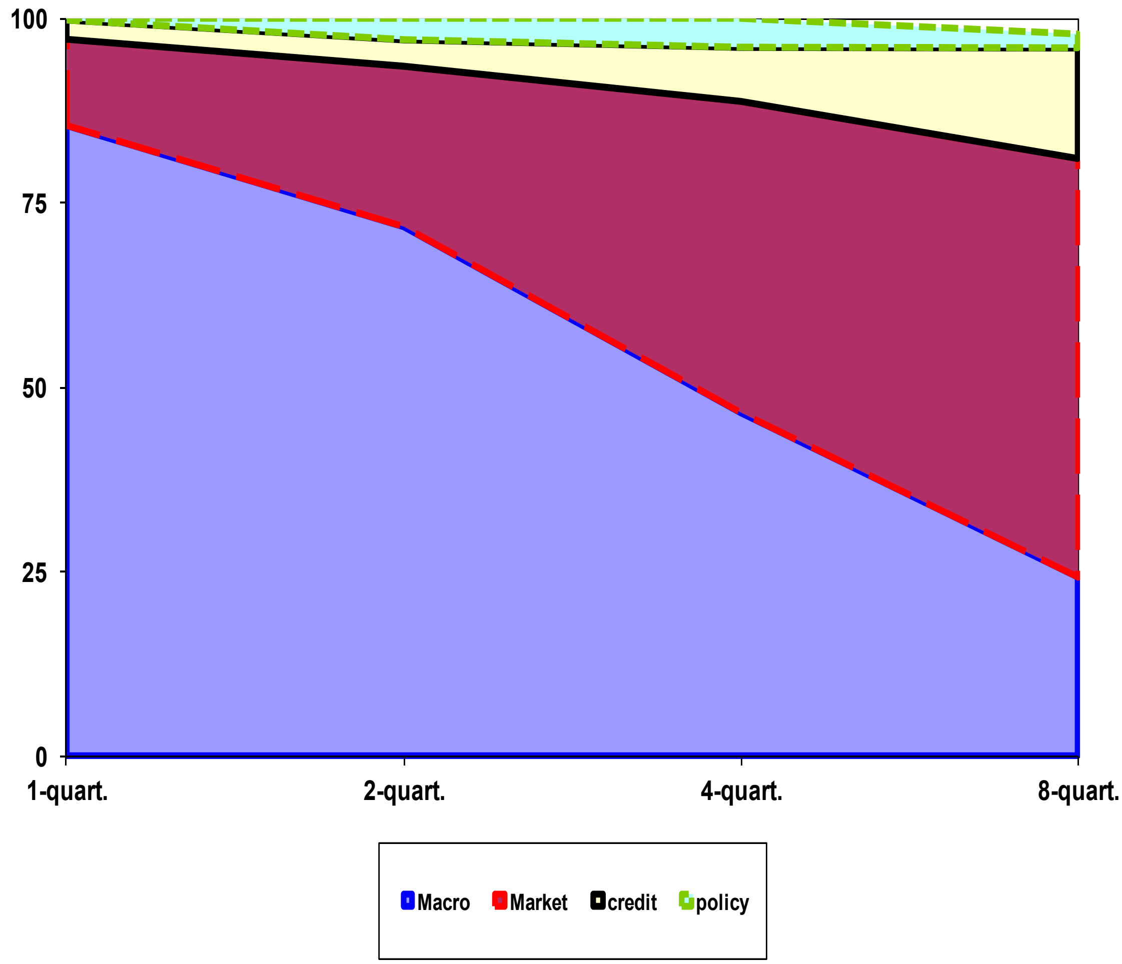


Figure 7. Response of GDP in model with period average asset prices (baseline ordering)

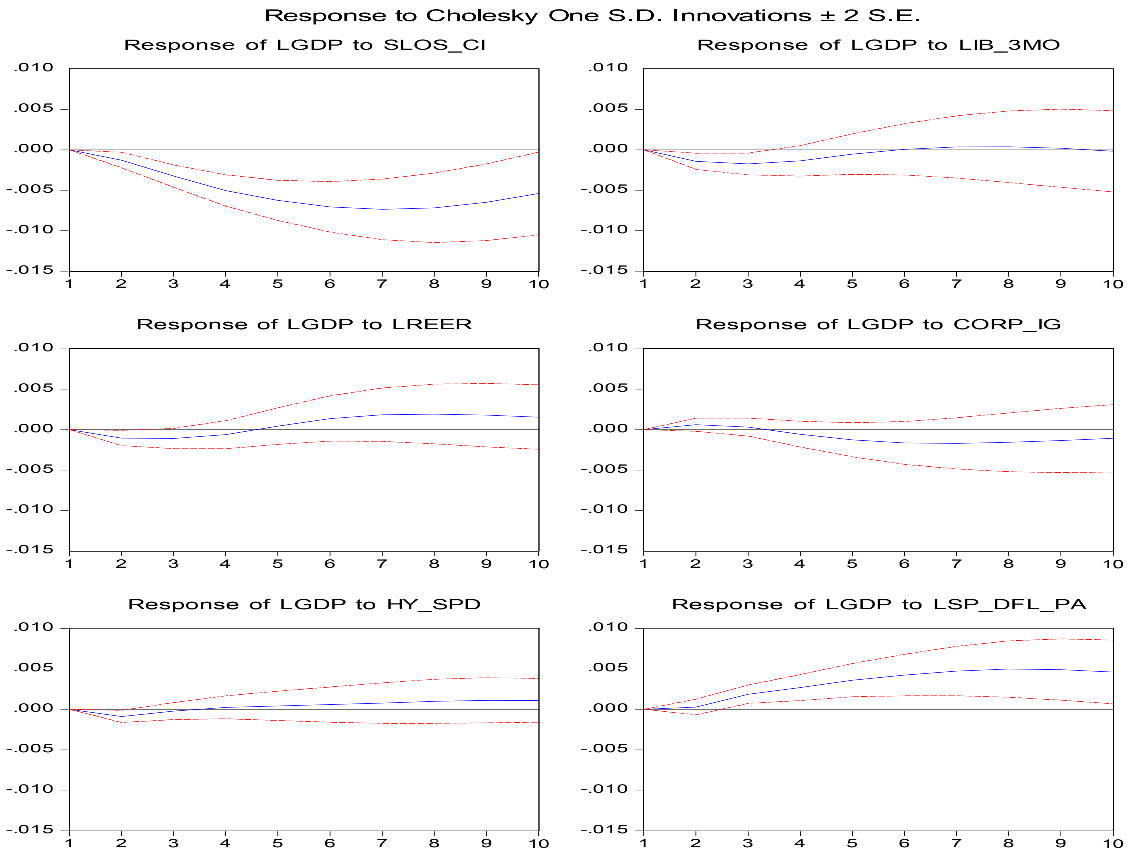


Figure 8. VDC of GDP in model with period average asset prices (baseline ordering)

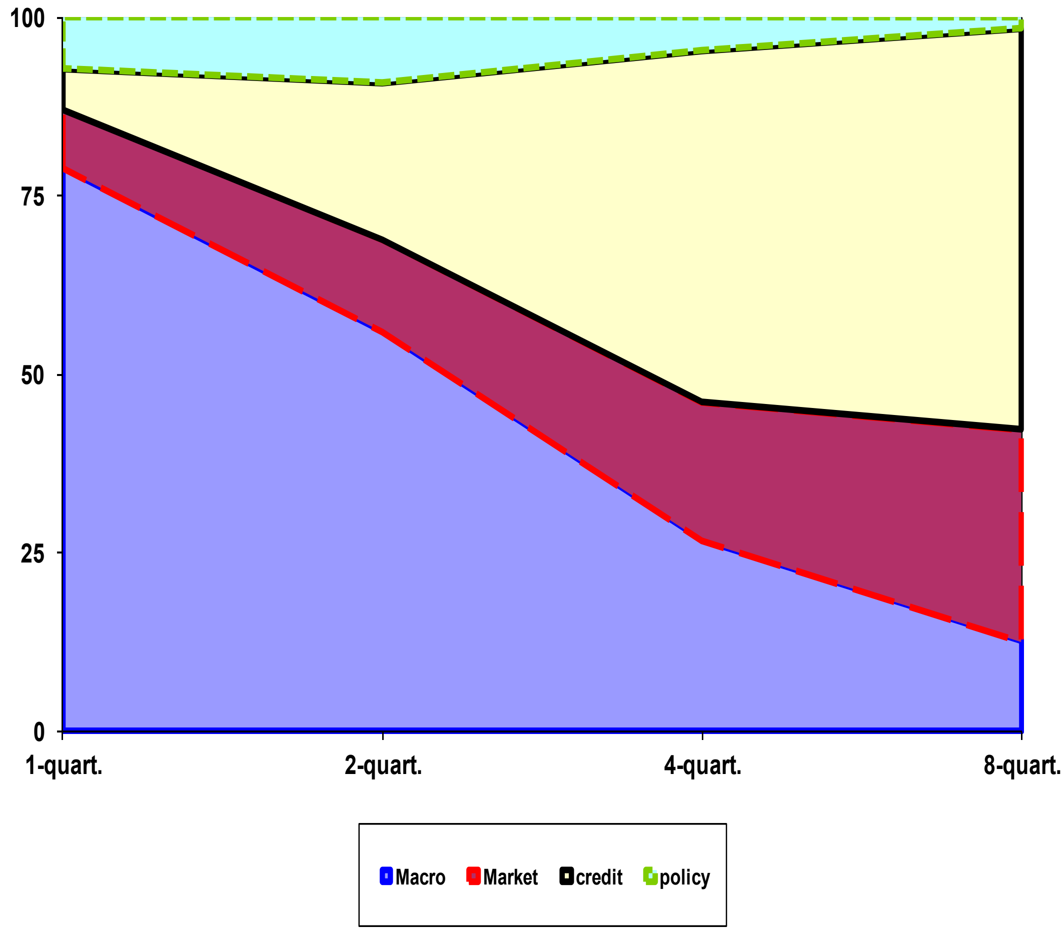


Figure 9. Response of GDP in model with period average asset prices (SLOS ordered after market variables)

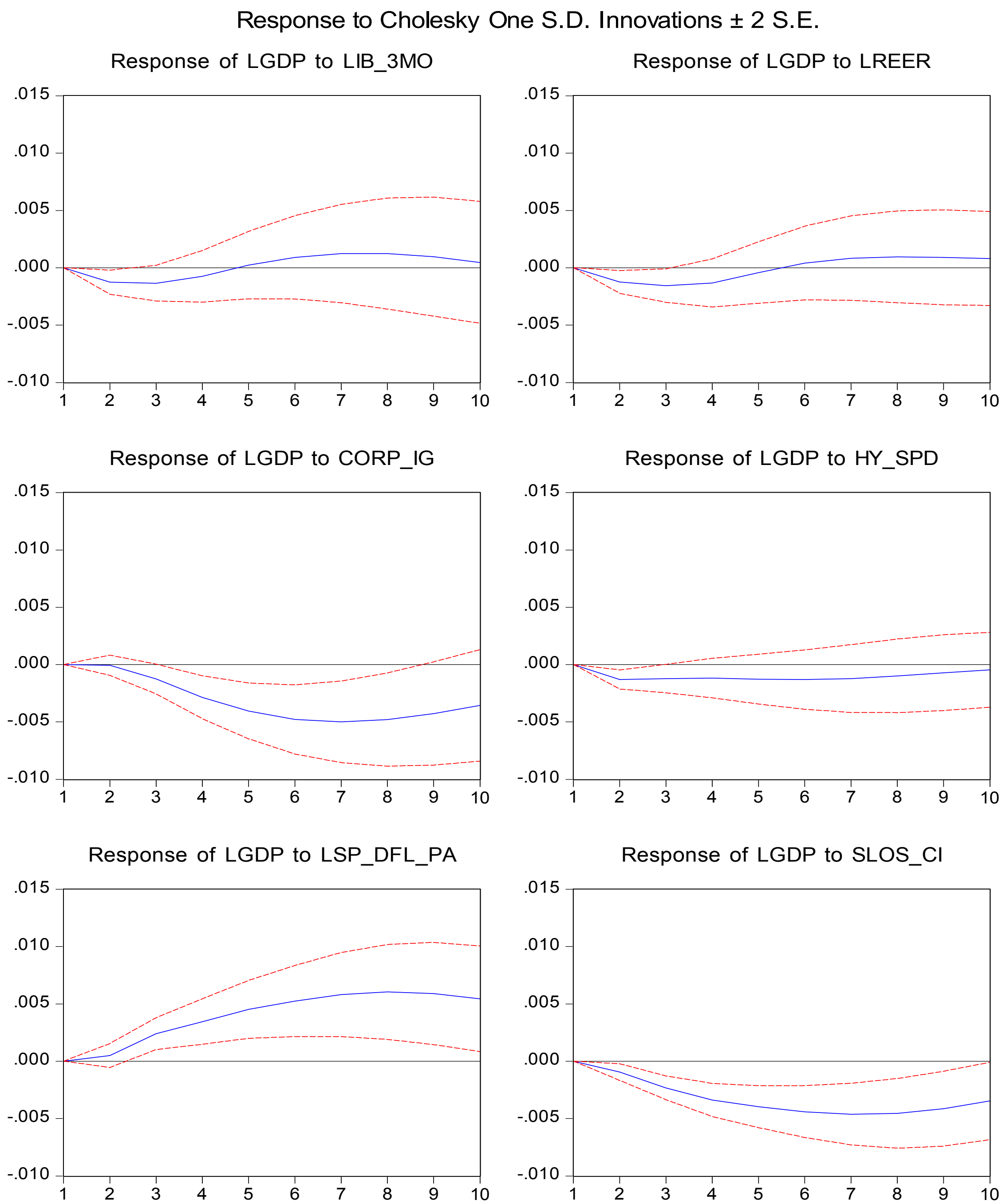


Figure 10. VDC of GDP in model with period average asset prices (SLOS ordered after market variables)

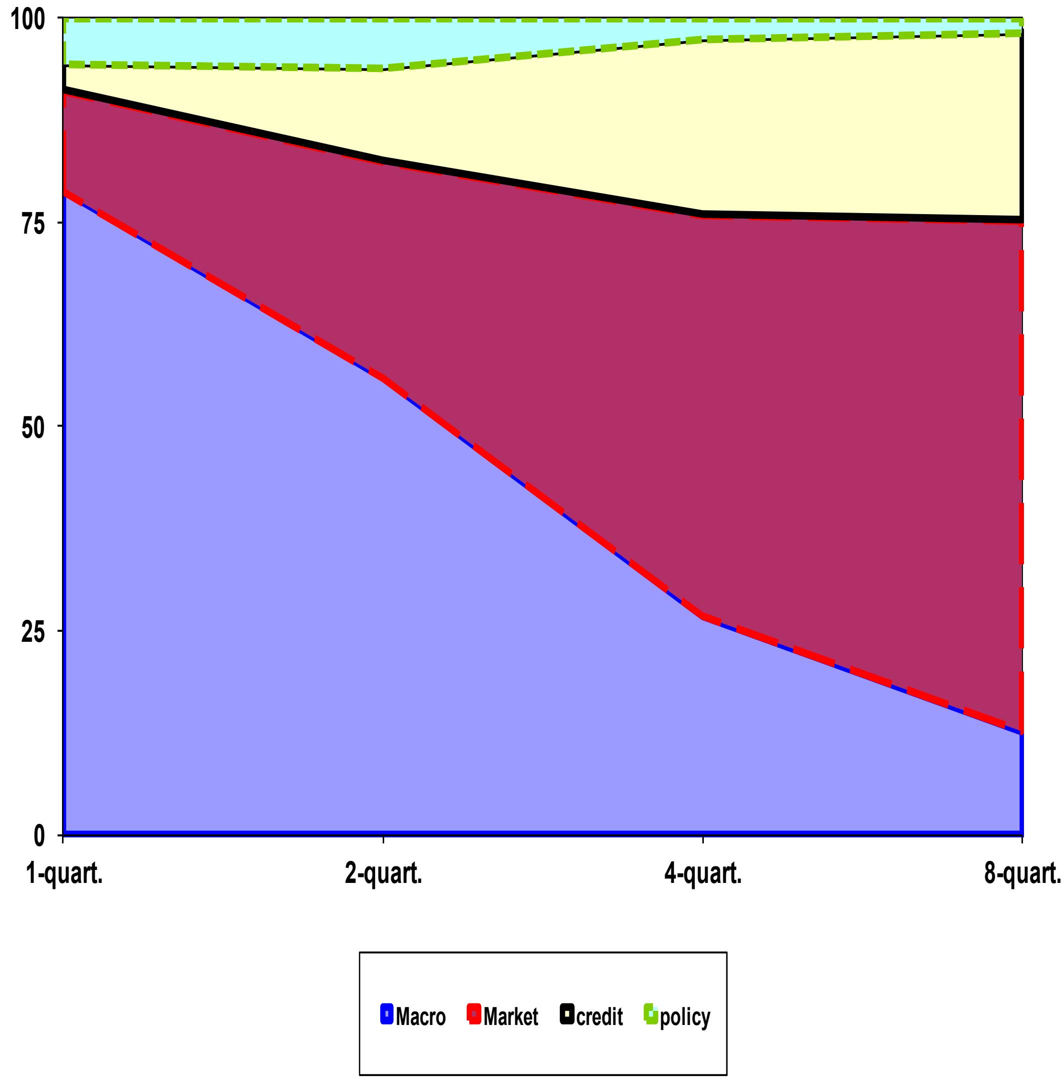


Figure 11. Variance Decomposition of Policy and Market Variables

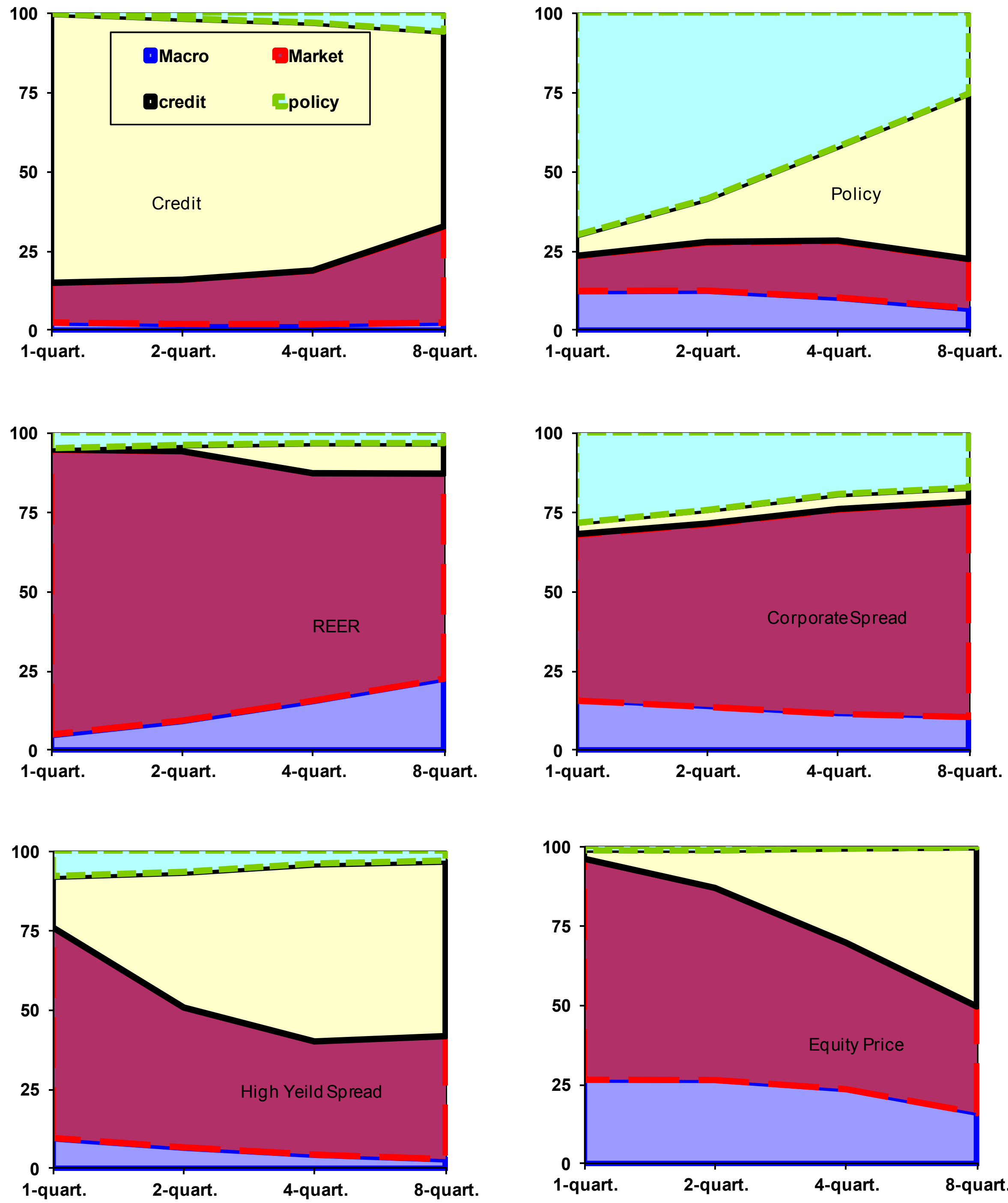


Figure 12. Response of market and financial variables to credit shocks

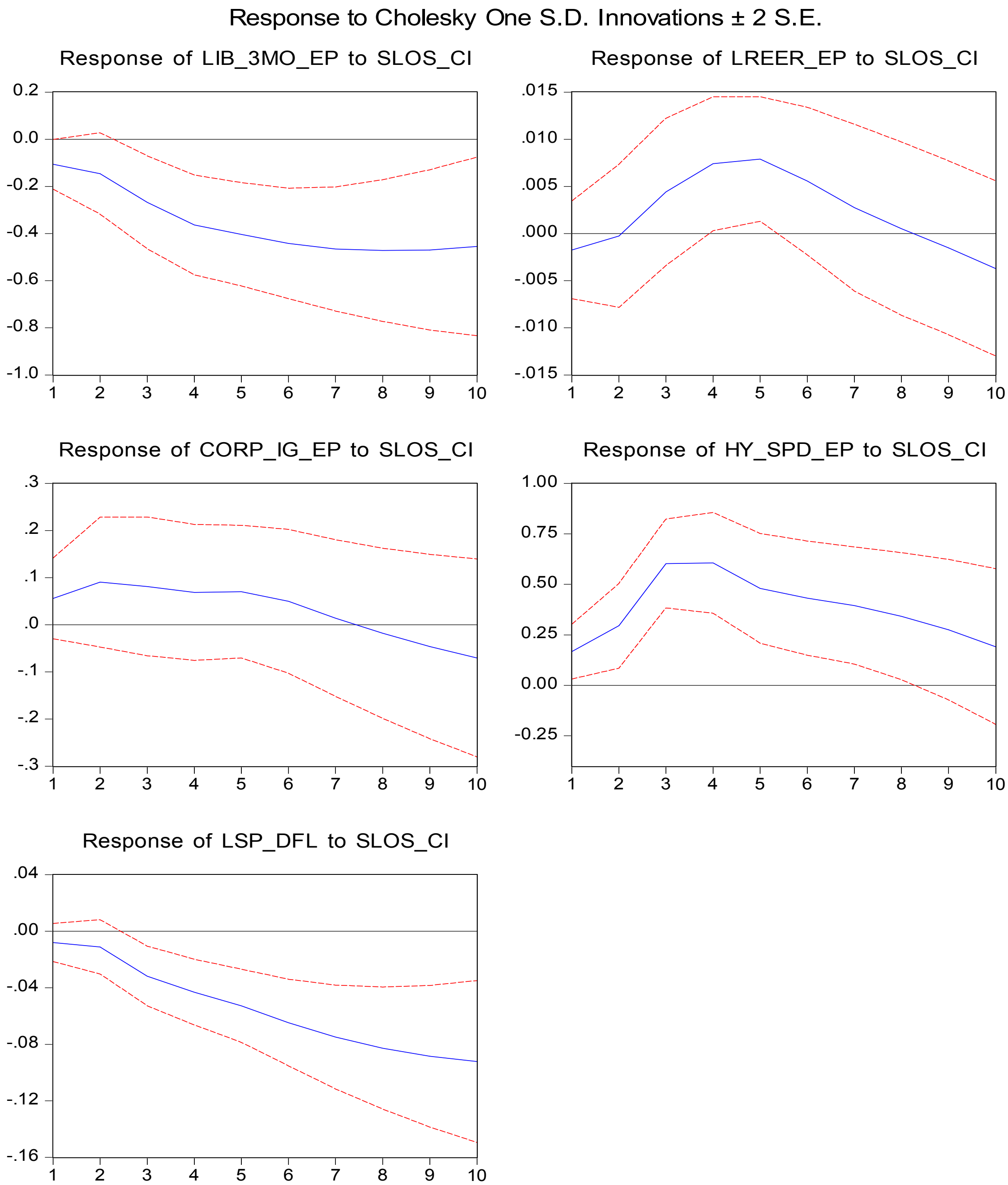
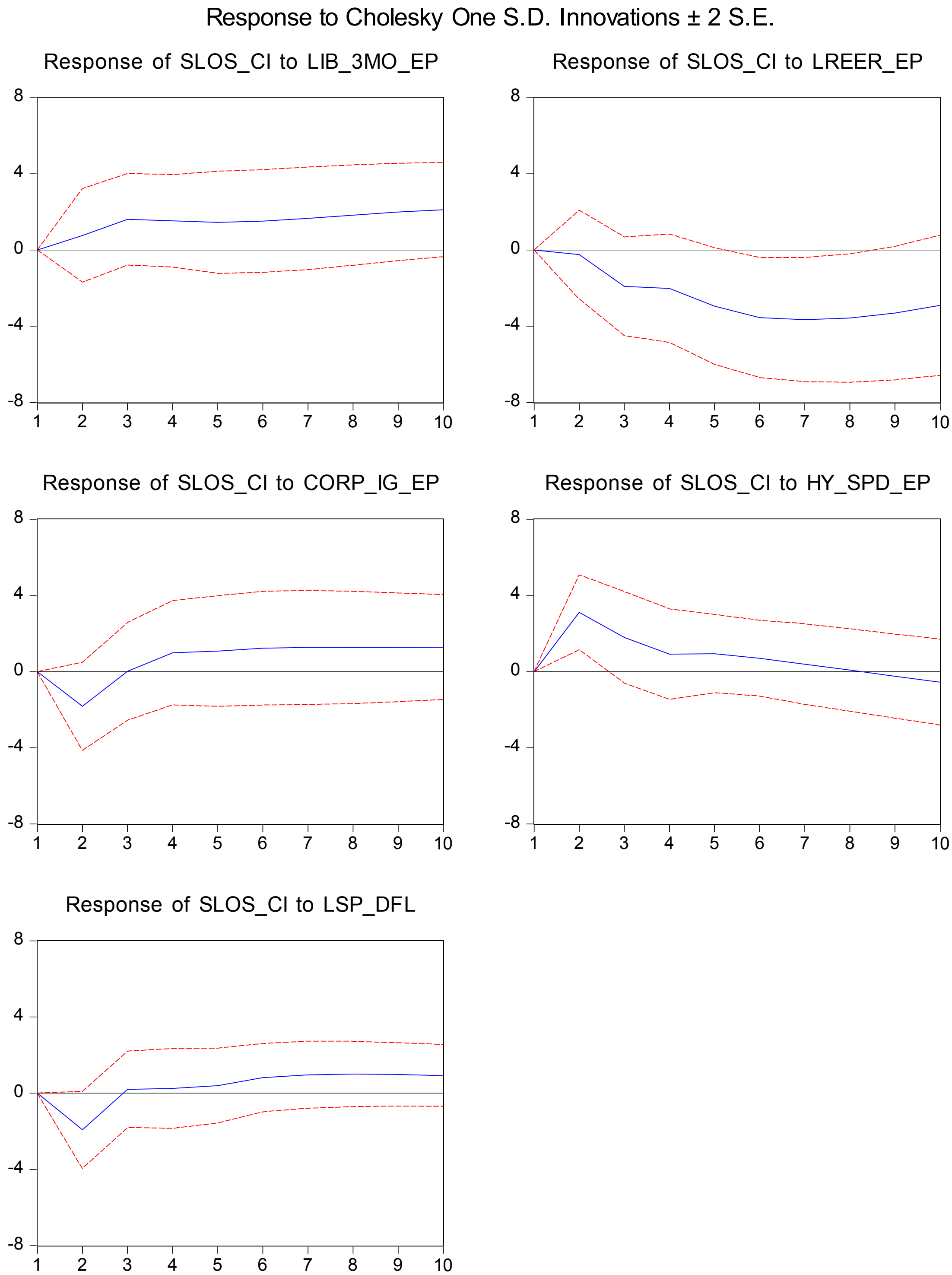


Figure 13. Response of credit to market and financial shocks



Appendix: Variance Decomposition Tables

Table A1. Decomposition for growth in baseline VAR

Variance Decomposition of Output (Baseline Ordering)									
Policy Rate									
Period	S.E.	LGDP	LPGDP	SLOS_CI	IB_3MO_E	LREER_E	FORP_IG_E	IY_SPD_E	LSP_DFL
1	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	82.0	0.1	7.4	0.6	6.1	0.1	3.6	0.1
3	0.0	63.2	0.1	19.8	4.7	6.0	0.1	3.9	2.1
4	0.0	46.5	0.4	33.7	5.8	3.9	1.1	3.3	5.2
5	0.0	34.9	1.4	41.2	5.6	3.4	2.6	3.7	7.1
6	0.0	27.6	2.5	44.6	5.3	4.4	4.0	4.5	7.2
7	0.0	22.6	3.3	46.5	5.0	5.7	5.0	5.2	6.6
8	0.0	19.0	3.8	47.9	4.7	7.2	5.6	5.8	6.0
9	0.0	16.2	4.2	48.7	4.6	8.9	6.0	6.2	5.4
10	0.0	13.9	4.5	48.9	4.5	10.6	6.2	6.4	4.9

Table A2. Decomposition for growth in VAR with both credit variables

Variance Decomposition in Model including both Credit Measures										
Period	S.E.	LGDP	LPGDP	SBS_CCE	SLOS_CI	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
1	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	79.5	0.2	1.8	7.4	0.7	7.5	0.4	2.4	0.1
3	0.0	59.3	0.2	1.9	21.2	5.5	7.1	0.3	2.8	1.6
4	0.0	42.1	0.2	2.7	35.6	7.0	4.8	0.8	2.2	4.6
5	0.0	30.4	0.7	4.6	43.3	7.1	3.7	1.7	2.3	6.2
6	0.0	22.8	1.4	7.7	45.9	7.0	3.9	2.5	2.5	6.3
7	0.0	17.6	2.0	10.7	46.8	6.9	4.4	3.1	2.9	5.6
8	0.0	13.9	2.5	13.2	46.8	6.9	5.1	3.4	3.3	4.9
9	0.0	11.2	2.8	15.1	46.5	7.0	6.0	3.6	3.5	4.2
10	0.0	9.1	3.1	16.6	46.0	7.0	7.1	3.8	3.7	3.6

Table A3. Decomposition for growth in various VARs

Variance Decomposition

Model includes only SBS

Period	S.E.	LGDP	LPGDP	SBS_CCE	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
1	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	85.1	0.4	2.6	0.2	5.5	0.7	5.1	0.3
3	0.0	71.5	0.3	3.6	2.9	5.3	5.0	11.3	0.2
4	0.0	57.9	0.3	5.2	4.0	3.7	13.9	14.8	0.2
5	0.0	45.8	0.8	7.3	4.0	2.5	22.5	17.1	0.1
6	0.0	36.6	1.2	9.7	3.4	2.3	28.3	18.3	0.1
7	0.0	30.1	1.6	11.8	2.8	3.0	31.4	19.2	0.1
8	0.0	25.5	1.8	13.6	2.3	4.0	32.6	19.9	0.2
9	0.0	22.2	2.0	15.0	1.9	5.2	33.0	20.3	0.3
10	0.0	19.7	2.2	16.0	1.6	6.4	33.0	20.6	0.4

Model With Period Average Asset Prices

Period	S.E.	LGDP	LPGDP	SLOS_CI	LIB_3MO	LREER	CORP_IG	HY_SPD	LSP_DFL_PA
1	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	78.8	0.0	5.7	7.2	3.9	1.3	2.8	0.3
3	0.0	55.2	0.7	22.0	9.2	4.2	0.8	1.5	6.4
4	0.0	36.1	1.9	39.1	7.2	2.8	0.8	0.9	11.2
5	0.0	23.7	3.0	49.3	4.6	1.9	1.5	0.7	15.3
6	0.0	16.5	3.6	54.2	3.1	2.1	2.2	0.6	17.8
7	0.0	12.2	3.9	56.1	2.3	2.5	2.5	0.6	19.9
8	0.0	9.8	4.1	56.5	1.8	2.9	2.5	0.7	21.6
9	0.0	8.3	4.2	56.2	1.5	3.1	2.5	0.9	23.2
10	0.0	7.5	4.3	55.6	1.4	3.2	2.5	1.0	24.6

Model With Period Average Asset Prices (SLOS Ordered After Market Variables)

Period	S.E.	LGDP	LPGDP	LIB_3MO	LREER	CORP_IG	HY_SPD	LSP_DFL_PA	SLOS_CI
1	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	78.8	0.0	5.6	5.4	0.0	6.1	0.8	3.2
3	0.0	55.2	0.7	6.1	7.1	2.9	5.8	10.8	11.4
4	0.0	36.1	1.9	4.1	5.9	10.1	4.8	18.6	18.5
5	0.0	23.7	3.0	2.6	3.8	16.8	4.0	24.6	21.5
6	0.0	16.5	3.6	2.1	2.6	21.0	3.4	28.2	22.7
7	0.0	12.2	3.9	2.0	2.1	22.9	2.9	30.9	23.0
8	0.0	9.8	4.1	1.9	1.9	23.6	2.5	33.1	23.1
9	0.0	8.3	4.2	1.8	1.7	23.6	2.2	35.0	23.0
10	0.0	7.5	4.3	1.7	1.7	23.4	2.0	36.7	22.7

Table A4. Variance decomposition for policy rate and REER in baseline VAR

Variance Decomposition of Policy and the REER (Baseline Ordering)										
Policy Rate										
Period	S.E.	LGDP	LPGDP	SLOS_CI	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
1	0.0	9.3	3.7	4.6	82.3	0.0	0.0	0.0	0.0
2	0.0	10.5	1.8	6.4	70.1	0.0	6.9	3.6	0.7
3	0.0	10.6	1.9	13.5	58.7	0.8	11.1	3.0	0.5
4	0.0	9.3	2.1	22.1	49.2	1.4	12.5	3.0	0.5
5	0.0	8.3	1.9	29.5	42.2	1.4	12.7	3.4	0.5
6	0.0	7.5	1.7	36.7	36.7	1.2	11.9	3.7	0.6
7	0.0	6.8	1.5	43.0	32.2	1.0	10.8	4.1	0.6
8	0.0	6.2	1.3	48.1	28.6	1.2	9.6	4.4	0.6
9	0.0	5.6	1.2	52.0	25.5	1.8	8.6	4.7	0.6
10	0.0	5.1	1.1	54.7	23.0	2.9	7.8	4.9	0.5
REER									
Period	S.E.	LGDP	LPGDP	SLOS_CI	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
1	8.7	0.0	0.2	0.6	7.0	92.2	0.0	0.0	0.0
2	11.6	0.4	4.4	0.3	4.9	85.4	0.1	0.0	4.5
3	13.0	0.4	8.8	1.9	3.8	78.4	0.5	0.1	6.1
4	14.3	1.3	11.4	5.6	3.4	71.3	0.7	0.2	6.2
5	15.4	2.5	13.0	9.2	3.3	64.8	0.7	0.5	6.0
6	16.3	3.2	14.1	10.5	3.5	60.9	0.9	0.6	6.3
7	17.1	3.6	15.2	10.4	3.6	58.0	1.1	0.7	7.3
8	17.7	3.9	16.6	9.8	3.5	54.9	1.6	1.0	8.7
9	18.2	4.3	18.1	9.3	3.3	51.6	2.0	1.4	9.9
10	18.7	4.9	19.2	9.4	3.1	48.1	2.4	2.2	10.7

Table A5. Variance decomposition for market variables in baseline VAR

Variance Decomposition of Market Variables
(Baseline Ordering)

Period	S.E.	LGDP	LPGDP	SLOS_CI	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
Credit Conditions									
1	0.0	0.0	3.6	96.4	0.0	0.0	0.0	0.0	0.0
2	0.0	0.1	2.3	84.6	0.4	0.0	2.5	7.3	2.8
3	0.0	0.1	1.8	82.2	1.9	2.2	2.0	7.7	2.2
4	0.0	0.3	1.5	81.1	2.7	3.8	2.1	6.7	1.9
5	0.0	0.5	1.3	78.0	3.2	6.9	2.3	6.1	1.7
6	0.0	0.7	1.2	73.6	3.7	10.9	2.6	5.7	1.7
7	0.0	0.9	1.1	69.1	4.3	14.5	2.9	5.2	1.9
8	0.0	1.1	1.0	64.9	5.1	17.6	3.2	4.9	2.1
9	0.0	1.3	1.0	61.2	6.0	20.0	3.5	4.6	2.3
10	0.0	1.6	1.0	58.4	7.0	21.3	3.8	4.5	2.4
Investment Grade Spread									
Period	S.E.	LGDP	LPGDP	SLOS_CI	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
1	0.5	6.8	12.6	1.8	29.6	2.7	46.4	0.0	0.0
2	0.7	5.3	10.5	3.6	28.4	2.1	50.0	0.0	0.0
3	0.9	4.4	9.5	4.3	24.4	7.2	49.4	0.8	0.1
4	1.0	3.7	8.9	4.4	21.4	14.3	45.5	1.4	0.4
5	1.2	3.3	8.4	4.7	19.4	20.2	42.3	1.3	0.5
6	1.3	3.0	8.1	4.6	18.1	24.6	39.8	1.3	0.5
7	1.4	2.8	8.0	4.4	17.4	27.7	38.0	1.2	0.5
8	1.5	2.7	8.0	4.2	17.2	29.4	36.8	1.2	0.5
9	1.6	2.6	8.1	4.3	17.3	30.1	35.9	1.1	0.5
10	1.6	2.5	8.2	4.8	17.6	30.1	35.2	1.1	0.5
High Yeild Spread									
Period	S.E.	LGDP	LPGDP	SLOS_CI	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
1	0.0	9.7	4.6	6.7	6.7	2.1	1.0	69.2	0.0
2	0.0	6.5	3.1	15.9	7.9	1.7	1.3	63.0	0.6
3	0.0	4.6	2.1	42.5	6.6	1.1	1.7	40.5	0.9
4	0.0	3.7	1.5	54.1	4.8	2.8	1.9	29.7	1.5
5	0.0	3.0	1.3	55.8	4.0	7.4	1.8	25.4	1.2
6	0.0	2.6	1.2	56.3	3.4	10.8	1.7	22.7	1.2
7	0.0	2.3	1.1	56.5	3.1	13.3	1.6	20.8	1.3
8	0.0	2.2	1.0	56.1	3.0	15.6	1.5	19.4	1.4
9	0.0	2.1	0.9	55.0	3.1	17.7	1.5	18.2	1.4
10	0.0	2.0	0.9	53.4	3.5	19.8	1.6	17.3	1.5
Equity Price									
Period	S.E.	LGDP	LPGDP	SLOS_CI	LIB_3MO_EP	LREER_EP	CORP_IG_EP	HY_SPD_EP	LSP_DFL
1	0.4	8.4	6.4	1.6	0.0	5.0	2.4	20.2	56.0
2	0.6	11.5	15.2	2.8	1.0	4.2	1.7	21.2	42.4
3	0.6	10.6	15.9	12.0	1.1	4.6	2.9	17.0	36.0
4	0.7	9.9	15.1	21.5	0.8	3.3	3.3	15.8	30.4
5	0.8	9.5	14.2	29.6	0.6	2.8	3.3	15.5	24.6
6	0.8	8.8	12.9	37.1	0.6	3.2	3.1	14.8	19.6
7	0.8	7.9	11.5	43.1	0.5	4.3	2.8	14.1	15.8
8	0.9	7.2	10.5	47.2	0.4	5.8	2.6	13.4	12.9
9	0.9	6.5	9.7	49.9	0.3	7.6	2.4	12.8	10.8
10	0.9	5.9	9.2	51.4	0.3	9.4	2.4	12.2	9.2