Mutual Fund Flows and Fluctuations in Credit and Business Cycles

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Abstract

We offer an early indicator for credit and business cycles, using within-family flow shifts towards high-yield bond funds. Our measure leads net fund flows across all asset classes a year in advance, thus forecasting future aggregate demand by fund investors. It positively predicts net bond issuance, growth in financial intermediary balance sheets, shares of high-yield bond issuers, the degrees of reaching for yield in the credit market, and changes in monetary policies as well as stock market returns and decreases in credit spreads. Importantly, our measure positively predicts GDP growth and negatively predicts unemployment earlier than other indicators in the literature that are based on credit spreads.

JEL Classification: E32, G12,

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1. Introduction

Understanding the role of the credit markets in economic cycles is a central issue in both macroeconomics and finance. On the one hand, credit markets are forward-looking by aggregating investor decisions through asset prices and thus provide useful indicators for future economic activities.[1] On the other hand, fluctuations in investors' demand for credit risk may drive the supply of funds in credit markets; which has important implications for firms' investment and production. As such, an emerging body of literature studies linkages between credit markets and business cycle fluctuation,[2] which also draw increased interests from regulators following the Great Recession.

In this paper we propose an early indicator for credit and business cycles, using investors' portfolio choices in high yield bond funds. It is a leading predictor, detecting fluctuations in economic activities earlier than other price or quantity based predictors suggested in the literature. Our measure is able to predict a wide range of credit cycle variables that have close links to economic activities. For example, it positively predicts the share of low quality bond issuers (Greenwood and Hanson, 2013) and the degrees of reaching for yield in the bond market, as well as growth in financial intermediaries' balance sheets (Krishnamurthy and Muir, 2015) and net amounts of total bond issuance. As a leading indicator for the business cycles, our measure positively predicts GDP growth and negatively predicts unemployment rates earlier than other measures suggested in the literature. In fact, its predictability as a leading indicator stems partly from its ability to predict credit spreads and Gilchrist and Zaerajsek's (2012) excess bond premium (EBP).

Our key idea is to dissect mutual fund total net flows along the dimensions of asset classes and allocations to separate out the flow component that is the most

[1] Numerous studies document that market prices predict future economic activities. See, e.g., Fama (1981), Harvey (1988), Estrella and Hardouvelis (1991), Gertler and Lown (1999), Ang, Piazzesi, and Wei (2006), Gilchrist,Yankov, and Zakrajšek (2009), Gilchrist and Zaerajsek (2012) among many others. See also Stock and Watson (2003) for a summary of the literature.
[2] See, for example, Gilchrist and Zaerajsek (2012), Krishnamurthy and Muir (2015), and Lopez-Salido, Stein, and Zakrajsek (2015).

sensitive to economic cycles. In particular, we focus on *intra-family* flow shifts opposed to *total net flows* typically employed in previous studies. Flow shifts are transfers or existing money across asset classes within a fund family and as such are most sensitive to investor beliefs. Total net flows on the other hand, are subject to various explicit and implicit costs incurred in sales and redemptions in and out of fund families and natural growth in asset under management.

We find that intra-family flow shifts into high-yield bond funds are the most sensitive component, and are able to predict a year in advance total net flows into various other asset classes. Thus, there seems to be a natural separation of investor flows in terms of their ability to predict fund investors' aggregate demand. One explanation for that is the fact that the investor base in high-yield bond funds is quite different from that in equity and other mutual funds. In particular, investors in high-yield bonds are wealthier, presumably savvier with more active research. Consequently, intra-family flow shifts towards high-yield bond funds seem as a cleaner and also earlier indicator than those based on total mutual fund flows (e.g., Feroli, Kashyap, Schoenholtz, and Shin, 2014).

Intra-family flow shifts are obtained from Investment Company Institute (ICI). In particular, ICI categorizes investor flows into "exchanges in," "exchanges out," "sales," and "redemptions," which aggregate to total net fund flows. Sales and redemptions are actual cash flows that enter or exit fund families, while exchanges in and out are flow shifts of *existing* cash within fund families. We focus on "net exchanges in and out" of high-yield corporate bond funds (hereafter, HYNEIO), which isolate changes in asset allocation decisions between high-yield credit and other asset classes.[3] We also define HYNSR, the sum of sales and redemptions components in high-yield corporate bond funds, which accounts for the vast majority of total net flows compared with HYNEIO. We verify that HYNEIO indeed captures early shifts in investor belief for future demand. In particular, we show that HYNEIO positively predicts, up to 12 months in advance, HYNSR as well as mutual fund flow components into the other asset classes, e.g., stocks, investment-grade and government bonds, and money market funds.

We start with investigating whether HYNEIO can predict variables that were found to be indicators for the credit cycle. We focus on Greenwood and Hanson's (2013) high-yield-share (HYS), which measures the quality of corporate bond issuers, and the degrees of reaching for yield (Baker and Ivashina, 2015). We conjecture that if HYNEIO predicts future investor demand, it can potentially predict credit market overheating associated with excess demand. We confirm our conjecture by showing that HYNEIO positively predicts the HYS over the next year. The univariate correlation between the HYNEIO and future HYS is around 0.60, showing strongly that investors' within-family portfolio choices predict a year in advance the shares of junk bond issuers in the economy. In contrast, an increase in the HYS does not positively predict an increase in HYNEIO. We also find that lagged HYNEIO predicts fractions of higher yielding securities within each rating category, or higher degrees of reaching for yield,[4] further showing that HYNEIO predict future excess demand and credit overheating.

We find similar results when we explore the ability of HYNEIO to predict business cycle indicators. In particular, we find that HYNEIO negatively predicts the default and high-yield credit spreads a year in advance, HYNEIO is also able to negatively predict Gilchrist and Zakrajsek (2012) excess bond premium (EBP) over a shorter horizon. We use this later on to motivate HYNEIO's ability to predict changes in business cycle earlier that other credit spread variables.

Next, we explore HYNEIO ability to predict credit cycle and business cycle variables. We start with growth in financial intermediaries' balance sheets and total net amounts of corporate bonds issued in the economy. To the extent that growth in leverage in financial sectors combined with negative shocks causes financial crises, as argued in, for example, Schularick and Taylor (2012) and also Krishnamurthy and Muir (2015), predicting the financial sector growth is a critical issue. We find a substantial

[4] We define a reaching for yield measure as average yield of corporate bonds in a given rating category divided by amounts-outstanding-weighted average yield of corporate bonds in the same rating category. Thus, the measure captures relative fraction of higher-yielding corporate bonds in a given rating.

forecasting power of HYNEIO for future growth in financial sectors' balance sheets: a one-standard-deviation increase in HYNEIO translates into a 0.75%-1.00% growth in intermediary balance sheets. In addition, HYNEIO positively predicts the next quarter's total net bond issuance. These results are quite robust even after we control for HYS and EBP, and other controls such as the term spread, the default spread, the three months T-Bill, the dividend yield, and cumulative past bond returns.

Building on the predictability of the credit variables, we examine the forecasting power of HYNEIO of GDP and unemployment rate (UER) in comparison to credit spreads and EBP in particular. For our variable to be a useful indicator beyond the existing predictors, it should be able to detect future booms and busts of economic cycles earlier than other variables. We find that this is the case. First, in a vector autoregression system (VAR), the impulse response analysis shows that a shock to HYNEIO predicts a positive spike in GDP growth and a negative spike in unemployment rates around three to five quarters in advance. In contrast, the existing predictors for business cycles, e.g., the EBP of Gilchrist and Zakrajsek (2012), predict future GDP growth and UER immediately over a period of one to two quarters. We verify the statistical significance of these timing differences using Wald tests for differences in impulse response functions. Second, in multiple regressions with various control variables known in the literature including term spreads, T-bill rates, credit spreads, the HYS, and the EBP, HYNEIO exhibits a strong forecasting power for GDP growth and unemployment rates. More importantly, HYNEIO can predict these variables up to 8 quarters into the future, consistent with the impulse response results, while the other variables fail to exhibit long-run predictability.

Changes in monetary policy can also trigger heavy fund inflows and outflows.[5] Consequently, we also examine whether HYNEIO predicts changes in future monetary policy or vice versa. Interestingly, we find that HYNEIO is able to predict future monetary policy changes, as measured by 2-year changes in the Fed's discount rate and

[5] For example, Feroli et al. (2014) argue that changes in monetary policy can trigger heavy fund inflows and outflows.

Romer and Romer's (2004) monetary policy shocks up to 12 months in advance, while monetary policy changes do not predict future HYNEIO.

Given that HYNEIO is a leading flow component, we turn to explore its ability to predict the stock and bond market returns. This could shed light on whether HYNEIO captures some quick moving demand component (or smart money) vs. slow moving (dumb money) flow components. Consistent with HYNEIO being a fast moving flow component, we find that HYNEIO is able to predict price continuation in both stock and bond markets. In particular, we find that HYNEIO positively predicts stock returns over a year and bond market index return over a period of 6-months. In contrast, equity flows (for the stock market) and HYNSR (for the bond market) show an indication of immediate reversals.

All these pieces of evidence support the notion that our measure of intra-family flow shifts towards high-yield bond funds predicts future demand by aggregate mutual fund investors, which is also the economic motivation of the measure. An alternative story is that HYNEIO itself is persistent noisy investor demand and thus can drive market prices and the state of the economy. Although we do not take a strong stance with respect to the exact underlying economic mechanism of possible alternatives, it is not likely that noisy investor demand is the underlying economic source. First, the dollar amounts of intra-family shifts are tiny compared with the dollar amounts of aggregate net flows and thus HYNEIO cannot exert substantial price pressure in the market compared with the total net flows. Second, investor clientele in high yield bond funds is quite different from the average retail clientele in equity mutual funds, which suggest that high-yield fund investors are typically more sophisticated investors, which we also confirm from communications with the ICI. In our robustness checks, we contrast HYNEIO with flow shifts into other asset classes, and find that only HYNEIO has forecasting ability, which suggests that portfolio choices in other asset classes do not carry useful information beyond information contained in HYNEIO.

Our results overall suggest a strong link between investors' portfolio choice in high yield corporate bond funds and fluctuations in credit and business cycles. Our paper distinguishes from previous in the following important ways. In a recent study, Lopez-Salido, Stein, and Zakrajsek (2015) show that investor sentiment is associated with economic activities. Their sentiment measure, however, is estimated in sample by projecting future credit spread changes on HYS and term premium. In comparison, ours is measured ex-ante, leads both HYS and term premium in predictability, and is also motivated from existing studies that link investors' noisy demand and their corresponding investment decisions in mutual fund markets.[6] Gilchrist and Zakrajšek (2012) show that the component of credit-spreads that is not explained by expected default probability, the excess bond premium or EBP, is a nice predictor of the business cycle. Not only HYNEIO leads EBP in terms of predicting future business cycles, but HYNEIO can also predict EBP itself.

2. Data

2.1. Aggregate Mutual Fund Flow Data

Our aggregate mutual fund flow data are obtained from the Investment Company Institute (ICI). The data period ranges from January 1984 to December 2012, a total of 348 months. ICI organizes the data in 33 distinct investment categories, as reported in Appendix A. We group asset class categories 10 through 17 into investment grade (IG) bonds, category 22 into high yield (HY) corporate bonds, categories 1 through 9 into equity (EQ), and categories 27 through 33 into government and money market funds (GM). The IG bond category includes pure and mixed (equity and bonds) funds investing in domestic and international markets.[7] In our empirical analyses, we focus mainly on the HY corporate bond category.

[6] There are numerous papers linking mutual fund flows to investor sentiment or noisy demand. For example, Goetzmann, and Massa (2003), Warther (1995), Coval and Stafford (2007), Frazzini and Lamont (2008), Baker and Wurgler (2002), Lou (2012), Khan, Kogan, and Serafeim (2013) among many others.

[7] We do not include categories 18 through 21 in the IG bonds, since they appear only for a shorter time horizon in our data. Also, excluding these funds does no materially change our results.

ICI categorizes investor net flows into four components: sales, redemptions, exchanges-in, and exchanges-out. The four components sum up to net fund flows. While most previous studies examine net flows (e.g., Warther, 1995), we decompose ICI's net fund flows into two materially distinct parts: net sales (sales minus redemptions, or SR hereafter), which capture actual money that enters or exit the fund family, and net exchanges (exchanges-in minus exchanges-out, or EIO hereafter), which captures transfers of existing money across asset classes within the fund family. As noted by Ben-Rephael, Kandel, and Wohl (2012), net sales mainly capture long term saving and withdrawals, while net exchanges are supposedly driven mainly by investors' asset allocation decisions.

Appendix B provides an example of the high-yield bond category from ICI data during 1998, the period of the Russian default and the Long Term Capital Management (LTCM) collapse. During the period, SR adds up to 14.63 billion dollars while the total EIO is a negative value of -1.02 billion dollars. Investors shifted their capital away from the high-yield category possibly due to the increased risk in the market during the LTCM collapse, while the total net flows into high-yield were large and positive (13.6 billion dollars). Using total net flows (13.6 billion dollars) or SR provides a quite different picture of investor demand from using EIO during the market turmoil.

2.2. Main Variable Construction

We construct monthly HYNEIO, which is the normalized exchanges-in minus exchanges-out (NEIO) of the HY category in a given month where normalization is based on the net assets of the HY category in the previous month, similar to Ben-Rephael, Kandel and Wohl (2012). This normalization allows us to account for the natural growth in the mutual fund industry during our sample periods. In a similar manner, we construct monthly HYNSR as the normalized sales minus redemptions (NSR) of the HY category, normalized using the net assets of the HY category of the previous month. In addition, we construct NEIO and NSR measures for the other asset classes, i.e., IGNEIO and IGNSR for the IG bonds, EQNEIO and EQNSR for EQ, and GMNEIO and GMNSR for the GM category. Figure 1 plots the 12-month moving averages of HYNEIO. HYNEIO captures important market events. The peaks and troughs of HYNEIO overlap with some the known credit events.

2.3. Summary Statistics

Table 1 reports the summary statistics and correlation matrices of NEIO and NSR across asset classes. We observe a few distinct characteristics of EIO and SR. In Panel A, for example, average HYNSR is 0.696%, showing increasing capital inflows into HY bonds during the sample period, while the average of HYNEIO is practically zero. The EQ, IG and GM categories present similar patterns; the averages of NEIO are around zero, while the positive averages of NSR reflect growth in assets under management. Panel B reports the monthly contemporaneous correlations of flow components *within* and *across* asset classes. Panel B.1 indicates that NEIO and NSR share a positive component, where the correlations range from 0.02 (GM) to 0.51 (HY). Exploring the correlation across asset classes, Panel B.2.1 indicates that HYNEIO, IGNEIO, and EQNEIO are all strongly and negatively correlated with GMNEIO, which suggest that investors shift money in and out of the GM category when investing in higher risk asset classes. In contrast, Panel B.2.2 shows that the correlations between NSR components are positive, showing that net flows into funds across different asset classes tend to commove together.

3. Intra-Family Flow Shifts and Business and Credit Cycle Indicators

In this section, we examine whether HYNEIO can predict other indicators for credit and business cycles suggested by prior literature. In particular, we focus on the following indicators: (1) the high yield share (HYS or LnHYS) of Greenwood and Hanson (2013), which measures the quality of corporate bond issuers and is found to have significant predictive power for future corporate bond returns; (2) a measure of reaching for yield (RFY) in the corporate bond market, in the spirit of Baker and

Ivashina (2015) which captures investor risk taking behavior and potential overheating in the credit market; and (3) we examine whether HYNEIO can predict aggregate credit spreads in general, and the excess bond premium (EBP) of Gilchrist and Zaerajsek (2012) in particular; where the latter has shown to have a strong predicting power for future economic activities.

In our analyses throughout the paper, we control for variables which were previously found to be important in predicting credit and business cycle variation. In particular, we control for the term spread (TS) calculated as the difference between long-term and short-term government bonds, the default spread (DS) calculated as the difference between Baa and Aaa corporate bonds from Moody's, the 3-months T-bill rate (TB), and the dividend yield (DY) calculated as the sum of dividends for past 12 months divided by the total market cap. In addition, throughout our tests, we contrast the predictive ability of HYNEIO with Greenwood and Hanson's (2013) high yield share (HYS) and Gilchrist and Zakrajšek's (2012) excess bond premium (EBP) since both (as mentioned above) are important predictors of the credit cycle and business cycle in the existing literature. Finally, we control for the excess returns on corporate bond indices.

Finally, we aggregate our flow component variables (i.e., NEIO and NSR) over a period of four quarters. By construction, this increases the persistent of these variables (e.g., Stambaugh 1999).[8] To alleviate any concerns that such persistence may bias coefficient estimates and *t*-statistics, we apply Amihud and Hurvich (2004) correction procedure. This has little effect on our results, which suggest that the persistent has a minor effect on our coefficient estimates and t-statistics. Moreover, we confirm that our series are not unit-root. For robustness, we also repeat our analysis with first differences.

[8] Stambaugh (1999) points out that high persistence (AR1 model) together with errors that are correlated with the error series of the dependent variable may produce a biased coefficient.

3.1 Predicting the Quality of Corporate Bond Issuers

According to Greenwood and Hanson (2013), the high-yield share of corporate bond issuers is a strong predictor for returns on corporate bonds. When credit markets are booming and risk premia are low, junk-quality firms can issue relatively more corporate bonds, which in turn predicts lower corporate bond returns. Lopez-Salido, Stein, and Zakrajsek (2015) use this measure of junk-rated issuer share as a proxy for credit market sentiment. We examine whether HYNEIO can predict the high-yield of share of corporate bond issuers.

The quality of bond issuers, or high yield share (HYS) is defined as the total amounts of corporate bonds issued by high-yield rated firms divided by the sum of total amounts of corporate bonds issued by both high-yield and investment grade rated firms. Specifically,

$$HYS_t = \frac{\Sigma_{HighYield} B_{it}}{\Sigma_{HighYield} B_{it} + \Sigma_{InvGrade} B_{it}}$$

where B_{it} denotes the amount of bond i issued in year t available in Mergent Fixed Income Database (FISD), using Moody's credit ratings. As in Greenwood and Hanson (2013), we use natural log of HYS (LnHYS) in regression analyses.

Table 2 presents the regression results.[9] In Specifications 1 through 3, we regress the average of LnHYS over four quarters on average HYNEIO over the past four quarters. We find that HYNEIO positively predict increasing shares of high-yield issuers. The results are quite robust to adding various control variables. The economic magnitude of the coefficient estimates on HYNEIO is also substantial. For example, a one-standard-deviation increase in HYNEIO is associated with a 3.8% increase in HYS, which implies that 3.8% of more junk-rated issuers in the economy.

We also examine the dynamic relation between HYNEIO and LnHYS using an annual VAR (vector autoregression) of HYNEIO and LnHYS with one lag of each

[9] In Table 2 we estimate the relation between HYNEIO and HYS and RFY levels. Using first differences of HYS and RFY yields qualitatively similar results.

variable. Figure 2 plots the impulse response functions. In particular, the response of LnHYS to a one-standard-deviation shock in HYNEIO is positive and significant, consistent with our predictive regressions in Table 2. This is consistent with HYNEIO moving first, capturing future demand in the credit markets and more high-yield bond issuance (Erel, Julio, Kim and Weisbach, 2012). In contrast, the response of HYNEIO to a one-standard-deviation shock in LnHYS, is negative and significant, suggesting that HYNEIO id trending down after an increase in LnHYS.

3.2 Predicting the Degrees of Reaching for Yield

We further examine whether HYNEIO can predict he relative amounts of higher-yielding corporate bonds in each rating category, which we interpret as a degree of reaching for yield (RFY) in corporate bond market (Baker and Ivashina, 2015). As Rajan (2013) and Stein (2013) note, an ultra-low interest rate environment can lead to reaching for yield by investors. For example, insurance companies will tend to hold higher-yielding bonds in a given rating category, since capital regulation is based on rating categories. Similarly, mutual funds' investment mandate is typically based on credit ratings, which also incentivize fund managers to hold relatively higher yield securities in a given rating category.

We define a measure of RFY for each rating j as the ratio of value-weighted average yield of all corporate bonds with rating j to equal-weighted average yield of the same corporate bonds:

$$\mathrm{RFY}_{jt} = \frac{\Sigma\, w_{jt} y_{jt}}{\Sigma \frac{1}{n} y_{jt}}$$

where the weight w_{jt} is determined by amounts outstanding of bonds. Note that this measure represents relative yields of corporate bonds outstanding, thus capturing an equilibrium outcome rather than investors demand for higher-yielding securities. The aggregate RFY measure is defined as simply averaging RFY across all rating categories.

Table 2 columns 4 through 6 present the regression results of RFY on lagged HYNEIO. We find that HYNEIO strongly predicts future RFY. A one-standard-deviation increase in HYNEIO is associated with a 5 to 5.5% increase in RFY. Moreover, controlling for other variables does not change HYNEIO's predictive ability. Interestingly, lagged LnHYS is marginally significant in predicting future RFY, which suggests that when HYS is elevated, RFY is probably at its peak. In addition, EBP's coefficient seems to have the opposite sign to what is expected.

In summary, the results provided in Table 2 show that our investor demand measure, HYNEIO, consistently predicts indicators which associated with the credit cycles.

3.2 Predicting Credit Spreads and Excess Bond Premium

Recent studies have found that credit spreads are important predictors for the business cycle variation. For example, Gilchrist and Zakrajsek (2012) argue that credit spreads represent not only the default risk of corporate issuers but also deteriorations in the capital position of financial intermediaries and resulting reduction in the supply of credit. Krishnamurth and Muir (2015) show that credit spreads are an important variable to predict the severity of financial crises when combined with growth in intermediary balance sheets. Exploring the credit spreads of high-yield corporate bonds, Gertler and Lown (1999) argue that the high-yield spread (i.e., the difference between the average spread of junk-rated bonds and Aaa bonds) has a significant explanatory power for the business cycle.

Given that HYNEIO is an early predictor for the HYS and RFY, an important and interesting question that arises is whether HYNEIO can predict credit spreads as well. We focus on the high yield spread (HY-Aaa) and the default spread (Baa-Aaa) as well as the excess bond premium (EBP), which is the difference between total corporate bond spread and the spread component that is predicted by expected defaults from the Black-Scholes-Merton model of credit risk.

Table 3 Panel A reports results of predictive regressions of future HY-Aaa and Baa-Aaa spreads on HYNEIO. In particular, we regress the one-year future spreads on lagged HYNEIO, lagged dependent variables, and other control variables. Our results show that HYNEIO negatively predicts both HY-Aaa and Baa-Aaa over the subsequent year, regardless of the specifications used. For example, a one-standard-deviation decrease in HYNEIO translates into a 0.56%-0.79% increase on the high-yield spread. In addition, HYNEIO is more economically significant for the high-yield spread which is not surprising given that the Baa-Aaa spreads have much smaller variation than HY-Aaa. Summarizing the results, a higher allocation of investor money into high yield funds predicts lower credit spreads for the next year.

Figure 3 depicts the impulse response functions from a quarterly VAR estimation of HYNEIO and HY-Aaa. The results are consistent with the regression results in Table 3. Interestingly, HYNEIO respond positively to a one-standard-deviation increase on the high-yield spread, which suggest that HYNEIO is trending down (i.e., investors shift portfolios out of high-yield bonds) when credit spreads are low and the credit market is at its peak, consistent with the notion that HYNEIO is an early indicator for credit cycles.

Table 3 Panel B provides the estimation results from the regression of quarterly average of EBP on lagged HYNEIO. Consistent with the results provided in Panel A, the regression coefficient on HYNEIO is negative and statistically significant at the 5% level. In other words, intra-family shifts of investor capital out of high-yield bond funds signal that the excess bond premium will increase in the next quarter. In contrast, we also find that EBP is not able to predict HYNEIO in unreported results.

To further examine the dynamic relation between HYNEIO and EBP, we estimate a quarterly VAR of HYNEIO and EBP on one-lag of each variable. Figure 4 depicts the impulse responses functions of the two variables to a one-standard-deviation shocks. A comparison of Figures (a) and (b) clearly indicates that HYNEIO has a significant effect on future EBP but not vice versa. A one-standard-deviation shock in HYNEIO translates to a decrease in EBP by more than 20 basis points over a period of a year, which is economically significant given that EBP's standard deviations is around 0.53.

4. Predicting Credit and Business Cycles Variables, Monetary Policy, and Return Predictability

In this section, we examine whether HYNEIO can predict other credit and business cycles variables, changes in monetary policy, and stock and bond market return predictability.

4.1 Growth in Financial Intermediary Balance Sheets and Total Amounts of Corporate Bond Issuance

A growing body of literature shows the importance of intermediaries' balance sheet for both the financial markets and real economy. Schularick and Taylor (2012) and Krishnamurthy and Muir (2015), for example, show that the severity of financial crises and recessions are closely related to increases in intermediary balance sheets and credit supply prior to crises. We measure growth in intermediaries' balance sheet as a quarterly difference in the financial sector's assets divided by the previous quarter's assets. The data is obtained from Table L.129 of the Federal Reserve Flow of Funds (see also Etula and Muir, 2014). In addition, we examine whether HYNEIO can predict growth in credit, as measured by the total net amount of corporate bond issuance (NBI), which we calculate as total amounts of bond issuance by nonfinancial corporate business out of total bond amounts outstanding, available from the flow of funds data from the Federal Reserve. Firms can take advantage of increasing demand for corporate bonds as measured by net flows to funds and issue more bonds. Thus, we expect that HYNEIO will positively predict future net bond issuance.

Table 4 reports the predictive regression results. In columns 1 through 3, we first regress quarterly growth in intermediary balance sheet assets (dA/A) on HYNEIO and other explanatory variables. The results indicate that HYNEIO is statistically and economically significant, regardless of the specifications used. A one-standard-deviation increase in HYNEIO, measured over the previous four quarters (*HYNEIO q-3:q*) translates into a 0.91% to 1.08% growth in intermediary balance sheets. The results are robust to controlling for past cumulative returns, which addresses the concern that price run-ups in corporate bonds drive both investors' portfolio shifts into high yield bonds and growth in assets of the financial sector.

In columns 4 through 6, we regress future NBI on HYNEIO. We find that the coefficient estimate on HYNEIO is positive and also statistically significant at the 5% level. The economic significance is also sizable. A one-standard-deviation increase in HYNEIO is associated with an increase in NBI by around 0.30%. These results are also robust to controlling for bond index returns, which takes care of the possibility that net bond issuance is driven by market timing in corporate bond markets (e.g., Baker and Wurgler 2002). Overall, the results in Table 4 suggest that HYNEIO is able to predict growth in the financial sector's balance sheet and net bond issuance.

Comparing the results in Table 2 with those in Table 4, we note that the predictability of HYS which is the ratio of high-yield bond issuance to total bond issuance is much stronger than the predictability of NBI. This is consistent with Erel, Julio, Kim and Weisbach (2012) who show that for non-investment grade borrowers, capital raising tends to be procyclical, while for investment grade borrowers it is countercyclical.

4.2 GDP Growth and Unemployment Rates

Having established that HYNEIO is a strong credit condition predictor, we examine whether HYNEIO can predict growth in GDP and changes in unemployment rates. We focus on the temporal properties of predictability in comparison with other existing predictors in the literature, by employing VAR impulse response analyses as well as multivariate regressions. In particular, we examine whether HYNEIO can predict business cycle fluctuations *earlier* than the EBP, which is a strong business cycle indicator.

In Panel A of Table 5, we present results from multivariate time series regressions of real GDP growth on HYNEIO and other control variables including HYS and EBP. In columns (1) through (4), we find that HYNEIO can positively predict real GDP growth for the next four quarters (*q+1:q+4*), suggesting that investors' switching into high-yield bonds signal stronger investor demand and economic growth. The results are quite consistent across all the four specifications in (1) through (4). To examine longer-run predictability of GDP growth, we also regress in columns (5) through (8) real GDP growth over the next eight quarters (*q+1:q+8*) on HYNEIO and other known GDP predictors. The results show that HYNEIO is able to predict GDP growth over a period of both four and eight quarters while EBP predicts GDP only in the first four quarters. Note that the coefficients on HYNEIO in (5) through (8) tend to be higher than those in (1) through (4), indicating that HYNEIO can predict both the first four quarter and the next four quarter GDP growth.

Table 5.A results suggest that HYNEIO is an early business cycle indicator by predicting GDP growth from five to eight quarters in advance. Alternatively, one can also interpret these results to imply that HYNEIO predicts more persistent and long-lasting component in GDP growth while EBP predicts more transient component. To further examine this issue and distinguish these two possibilities, Figure 5 plots the orthogonalized impulse responses of real GDP growth to a one-standard-deviation shock in HYNEIO (4.a) and EBP (4.b). A comparison of Figures 4(a) and 4(b) reveals that HYNEIO is an earlier indicator, compared to EBP. A one-standard-deviation shock in HYNEIO leads to an initial change in GDP growth only after three quarters. In contrast, Figure 4(b), indicates that a one-standard-deviation shock in EBP affects GDP immediately starting one quarter after the shock, over a period of two quarters.

We verify that these time differences are statistically significant using Wald tests for differences in impulse response functions. In particular, we use Monte-Carlo simulations to calculate the impulse response function confidence intervals. These simulations allow us to calculate the Wald tests.

Recall, that EBP's impulse response is calculate for a negative 1 SD shock, so that both impulse response functions would be comparable. We find that the difference in HYNEIO and EBP impulse response functions for quarters 1 and 2 is -0.002 with a *p*-value of 0.026. This confirms that EBP moves first. Similarly, the difference for quarters 3-5 is 0.0031 with a p-value of 0.022. These tests confirm that HYNEIO is an early indicator.

In Panel B of Table 5, we focus on changes in unemployment rates using HYNEIO. Similar to Panel A, we report the estimation results for both first four quarters (columns 1 through 4) and eight quarters (columns 5 through 8). We find qualitatively similar results to those we find from the GDP predictability analyses. In particular, the coefficients on HYNEIO are highly statistically significant in both first four quarters and eight quarters, while the coefficient on EBP is significant at the 5% level only during quarters 1 through 4.

In Figure 6, we provide impulse responses of changes in unemployment rates to further examine whether HYNEIO is a persistent predictor for unemployment or an early predictor. As in Figure 5, the impulse responses indicate that a shock in HYNEIO leads to a negative peak only after four quarters, while a shock in EBP appears immediately. Although noisier, the Wald tests confirm that EPB moves first in quarters 1-2 (a p-value of 0.017) while HYNEIO kicks in in Quarters 4-7 (a p-value of 0.097). Overall, these results confirm that HYNEIO is an early indicator of business cycles.

4.3 Predicting Future Monetary Policy

Given that HYNEIO is able to predict both credit and business cycle fluctuations, we now examine the relation between HYNEIO and monetary policy changes. In particular, does HYNEIO predict changes in monetary policy or vice versa? The answer to this question is also informative about uncovering the source of the predicting power of HYNEIO. If we find results that HYNEIO can predict future monetary policies but *not vice versa*, the results lead us closer to a smart investor channel through which the predictability of credit and business cycles operates.

We use two measures of monetary policies: changes in the Fed's discount rate (lending rate at the discount window) and also changes in Romer and Romer's (2004) measure of monetary shocks (R&R), the latter of which captures unexpected shocks in Fed policies.[10] [11] Given the persistent nature of changes in monetary policy, we focus on a two year horizon, where we regress future 24 months changes in discount rates and the R&R measure on HYNEIO and other explanatory variables including EBP and HYS.

Table 6 presents the regression results. Columns (1) through (3) indicate that both HYNEIO and log HYS positively predict future discount rate changes, even after controlling for lagged monetary policy changes and other control variables. HYNEIO is also economically significant. A one-standard-deviation shock is associated with a 0.60% change in future discount rates depending on the specification used.

To further examine the timing of predictability, we regress future 24-months discount rate changes on explanatory variables by skipping the first 12 months, shown in columns (4) through (6). In other words, we regress discount rate changes from 13 to 36 months ahead on current variables. The results shown in (4) through (6) indicate that HYNEIO coefficient remains positive and significant, while HYS loses its predicting ability, thus showing that HYNEIO is an early predictor for monetary policies. We find qualitatively similar results in columns (7) through (10) when we regress future changes in R&R on HYNEIO. Note also that throughout all specifications in (1) to (10), HYNEIO is the only predictor that remains statistically significant at the 10% level. Finally, in an untabulated VAR analysis we find that changes in monetary policies do not predict future HYNEIO. Combined, our results show that HYNEIO is a strong early indicator for future monetary policies as well.

[10] Although the Fed fund rate is also available, the data is cleaner for the discount rate. Nevertheless, for the most part, the two rates are very similar.

[11] The measure up to 1996 is available on the Romer and Romer website and also is available up to December 2007 in the following website: http://www.basilhalperin.com/blog/2013/12/updated-romer-and-romer-2004-measure-of-monetary-policy-shocks/.

4.4 Predicting the Stock and Bond Market Returns

Ben-Rephael, Kandel and Wohl (2012) equity demand, measured by EQNEIO, is positively and strongly associated with stock market price changes. If HYNEIO is an early demand indicator, and an increase in demand for high-yield bonds predicts future increase in demand for equity, HYNEIO might explain future changes in prices in the stock market.[12]

Table 7 reports results from multivariate regressions of future stock market returns on HYNEIO and other control variables. Specifically, we regress future 4-quarter excess market returns on lagged HYNEIO and EQNEIO controlling for lagged returns on both the stock market and high-yield bond index. Column (1) indicate that long-term EQNEIO measured over four quarters has no significant predictive power for future 4-quarter stock market returns. This result is consistent with Ben-Rephael, Kandel, and Wohl (2012) who argue that EQNEIO captures short-term investor sentiment.[13] In contrast, Columns (2) to (6) indicate that HYNEIO positively predicts future stock market returns, which is both statistically and economically significant. A one-standard-deviation increase in HYNEIO is associated with a 5-6% increase in excess market returns. As hypothesized, this is consistent with HYNEIO leading equity demand, which is positively associated with equity prices (see Table 9 for details analysis).

Overall, the results presented in Table 7 show strong predictability of stock market returns using HYNEIO. To the extent that stock market leads real activities, these results are also consistent with the notion that HYNEIO can be a useful early indicator for the business cycles. More broadly, these results contribute to the discussion raised in Collin-Dufresne, Goldstein and Martin (2001) who argue that the weak linkage

[12] In Table 9 we explore the lead-lag relation between HYNEIO and other asset classes' flows and show that HYNEIO positively predict flows into equity mutual funds up to a year in advance.

[13] The authored show that short-term EQNEIO measured over a period of a quarter is able to predict reversals in the stock market over a period of 4 months.

between the stock and credit markets can be due to independent demand/supply shocks in both markets. We find that HYNEIO leads equity market flows (Table 9). Thus, our findings provide a link between demand shocks in credit and equity markets. Along these lines, Gilchrist and Zakrajšek (2012) find that their excess bond premium (EBP) is also able to predict the stock market and link that to the risk bearing capacity of investors in the market.

Next, Table 8 explores the relation between HYNEIO and bond index returns. We focus on both the High-Yield and the average investment grade bond indices. To point out the differences between net-sales (HYNSR) and net-exchanges (HYNEIO) in this table, we also present results for HYNSR (we contrast HYENIO with other flows variable in Section 5). The results indicate that HYNEIO is able to positively predict future bond market returns, controlling for the index return and other variables used in our previous regressions. Interestingly, the predictability is around 6 months followed by reversal in bond returns. Interestingly, HYNSR show no signs of continuation. In fact, HYNSR present a significant reversals starting after four quarter. Table 9 analyzes directly the lead-lag relation between HYNEIO and HYNSR, and shows that HYNEIO leads HYNSR. This again suggests that HYNEIO provides earlier information for demand than HYNSR. Consequently, HYNEIO is able to predict further continuation on the bond market. Once the demand subsides prices revert, consistent with Greenwood and Hanson (2013).

At a broader level, Ben-Rephael, Kandel and Wohl (2012) provide evidence that equity flows are dumb. That is, quarterly EQNEIO is followed by a short-term stock market reversal. Tables 7 and 8 provide further indication that HYNEIO is smart in the sense that it is able to predict returns in the same direction over horizons of 6 to 12 months. Interestingly, HYNSR appear as dumb in the sense that an increase in HYNSR is followed by a reversal pattern.

5. Exploring HYNEIO predictive ability and Robustness Tests

The evidence so far suggests that HYNEIO is an early indicator. In this section we want to shed light on HYNEIO predictive ability. We start with exploring the lead-lag relation between HYNEIO and other asset classes' flow components, and continue with decomposing HYNEIO sources. Then, as part of our robustness tests, we contrast HYNEIO with other asset classes' NEIOs and NSRs, and explore HYNEIO predictive ability over time.

5.1 Lead-Lag Relations of Fund Flows Among Asset Classes

In this section we establish empirically that intra-family flow shift into high yield bonds (HYNEIO) leads flow shifts and net flows in and out of all the other asset classes. This analysis provides the necessary condition for HYNEIO to be a leading demand component. We discuss later on in Section 6 the institutional features of high yield bond funds and their investor clientele, which sheds light on the reasons for an early response of investors in this asset class. By comparing the lead-lag relations, we show that this particular fund flow component, HYNEIO, predicts and thus leads all the other various components of investor flows, not vice versa. This lead-lag analysis will also show the importance of decomposing total net flows and separating out HYNEIO in comparison with the usual total flow measures employed in previous studies (e.g., Feroli et al, 2014).

In Table 9, we regress each of these future flow components on all the other flow components. We also make sure to control for past cumulative returns of each asset class. We start with contrasting the HY and IG category (Panel A). Column (1) and (4) show that HYNEIO predicts future HYNEIO, indicating HYNEIO is persistent. We also find that HYNSR (net redemption and sales in HY funds) marginally predicts future HYNEIO over subsequent 4 quarters (Column (4)), but with a *negative* sign. That is, an increase in HYNSR predicts a future decrease in HYNEIO. No other flow components exhibit predictability of HYNEIO. On the contrary, HYNEIO predicts future increases in all the other flow components (HYNSR, IGNEIO, and IGNSR) in columns (2) through (4) and (5) to (8). These results confirm that, across the four flow variables, HYNEIO leads all other flow variables, and not vice versa. In addition, lagged returns do not predict future HYNEIO, while they predict future HYNSR.

Contrasting HYNEIO with equity flows (Panel B) we consistently find that HYNEIO positively predict all other flow variables. Interestingly, equity returns negatively predicts HYNEIO, which shows that higher returns in the equity market are followed by investors moving out of HY funds. This result also indicates that the clientele of HY funds are different from equity funds. Ben-Rephael, Kandel and Wohl (2012) show that EQNEIO is mainly due to investor sentiment and thus HY investors move out of risky securities when sentiment is high, suggesting that these HY investors are smarter than equity investors (as confirmed in Tables 7 and 8). Finally, Panel C also shows that HYNEIO leads shifts from government and money-market (GM) funds and not vice versa.

In sum, Table 9's findings support our view that HYNEIO better captures early shifts in investor demand.

5.2 Where Does Flows to High Yield Come From? Decomposing the Predictive Power of HYNEIO

By construction, investor dollar amount of flow shifts into high yield bonds should be offset by flow shifts out of other asset classes. In this section, we decompose HYNEIO into its sources to explore whether the predicting power of HYNEIO is driven mainly by a specific source of an asset class. This analysis will further help understand the source of HYNEIO predictability.

To this end, we categorize asset classes into the four major groups (i.e., IG, HY, EQ, and GM) and the residuals of all the major asset classes (O). Thus, we have:

$$(\$\ Net\ Exchanges\ in\ HY) + (\$\ Net\ Exchanges\ \mathrm{in\ IG}) + (\$\ Net\ Exchanges\ in\ GM) + (\$\ Net\ Exchanges\ in\ O) = 0$$

By dividing total assets in the high-yield category, we can then rewrite net changes in high yields (HYNEIO) as (after rearranging)

$$HYNEIO = -(EQC + IGC + GMC + OC)$$

where the four components on the right, EQC, IGC, GMC, and OC, represent net exchanges in and out for each of the four other asset classes, normalized by total assets in the high-yield category. Using this decomposition, we can examine where the predictive power of HYNEIO is coming from. In particular, we regress the future credit and business cycle variables on these four components of HYNEIO.

Panel A of Table 10 presents results from the regressions of future credit and business cycle variables on the four HYNEIO decompositions. We make the following two observations. First, it is difficult to conclude that any one of the four components has a dominant predicting power. There are some cases where one variable is statistically significant over the other, but there is no strong pattern. Second, the coefficients are all in the same signs and the economic magnitudes seem similar, and coefficients are not statistically different from each other. Moreover, the coefficient magnitudes depend on the magnitude of the net exchanges. Thus, in terms of 1 SD effect, the differences are much smaller.

In conclusion, the decomposition analysis shows that the predictability is not due to investor flow shifts from one particular asset class to high yield bonds. Rather, it is the collective shifts into high yield funds that matter. In other words, there is something unique about flow shifts into high yield bond funds (regardless where they come from), that is probably driven by the differences in investor clientele.

5.3 Contrasting HYNEIO with other Asset Classes' NEIOs

Next, to explore the robustness of our results, in this section we run a horserace between all asset classes' flow shifts (i.e., net-exchanges), namely, HYNEIO, EQNEIO, IGNEIO, and GMNEIO. Panel B of Table 10 reports the results.

Importantly, across all the columns (1 through 8), we find that HYNEIO is statistically significant at the 5% level in predicting future variables in the presence of other NEIO variables and control variables. In contrast, the other NEIO variables, e.g., EQNEIO and GMNEIO are not statistically significant at the 5% level in any of the columns. The only exception is IGNEIO for which we find the regression coefficients are statistically significant in columns (1) and (4). However, the coefficients have the opposite sign. Thus, the results in Panel B show that HYNEIO beats within-family flows to other asset classes, consistent with HYNEIO being an early demand component.

5.4 Contrasting HYNEIO with Asset Classes' NSRs

In Table 11 we contrast HYENIO with HYNSR (Pane A) followed by a horserace between HYNEIO and other asset classes' NSRs (Panel B).

The fact that HYNEIO predicts HYNSR, suggests that when HYNSR is alleviated credit or business conditions are alleviated. Panel A results indicate that this seems to be the case. In particular, Specifications (1) – (6) reveal that HYNSR is not able to predict all variables predicted by HYNEIO. On the other hand, since GDP and UER conditions last for more than a few quarters. Thus, is not surprising that HYNSR is able to predict GDP and UER. Importantly, when we put both variables together in a VAR system and account for the fact that HYNEIO leads HYNSR, HYNSR loses its predictive power (see Appendix C for more details). Finally, adding other NSR flow components in Panel B of Table 11 doesn't affect HYNEIO predictive ability; and consistent with Panel 10.B results, other flow components do not show the same predictive ability.

5.5 HYNEIO Predictive Power for Rolling Subsamples

To investigate the importance of high-yield mutual funds, we explore how HYNEIO predictive ability varies over time using rolling window regressions. In particular, we use 15-year intervals (60 quarterly observations in each interval) and regress our main credit and business cycle variables on HYNEIO controlling for other variables. We then plot the estimated regression coefficients in Figure 7. In general, the results show a stronger trend in coefficient estimates. One reason for this trend could be driven by the fact that high-yield corporate bond mutual funds have grown substantially over time, and is around 250 billion dollars in terms of AUM in last year of our sample.

6. Putting HYNEIO on the Left Hand Side and Discussion

6.1 HYNEIO on the Left Hand Side

Our results provide robust evidence which suggests that HYNEIO is able to predict a battery of credit cycle and business cycle variables. In particular, HYNEIO is able to predict known predictors such as credit spreads and the HYS. Given these results, a natural question is "what affects HYNEIO?" Given that some of the relations were already discussed (e.g., EBP), in this section we want to explore the predictive power of the variables that were previously explained by HYNEIO.

We run our tests in a VAR like setting, where we control for lagged HYNEIO and lagged high-yield returns. Then, in each specification we include one additional variable. We also explore the relation between HYNEIO and the average level of the VIX index. Since optimal portfolio choice by rational investors between equity and corporate bonds depends on risk, we include the VIX as a measure of change in risk;[14]

Table 12 reports the results. We find that HYNEIO is not responding to past bond returns. Thus, the change in demand is not driven a feedback response. We find that LnHYS negatively predicts HYNEIO (consistent with Figure 2's findings), which clearly shows that HYS does not lead in predicting credit cycles. In other words, when HYS is elevated, HYNEIO is starting to trend down. We also find that HYNEIO

[14] We use the VXO is based on the implied volatility of the S&P100 options, available from 1986 and highly correlated with the VIX.

respond to the other variables in a similar manner. For example, DiffLnRealGDP negatively predicts HYNEIO, and DiffUER positively predicts HYNEIO. This again is consistent with HYNEIO being a leading indicator. That is, When GDP is elevated or UER is low, HYNEIO is already trending down. Interestingly, HYENIO negatively respond to changes in monetary policy and stock market returns; suggesting that HYENIO is trending down after market run-ups or when the fed increases rates to prevent overheating. Finally, we do not find a relation between HYNEIO and VIX in this setting.

In sum, HYNEIO is able to predict a battery of important variables, and is the cases that HYNEIO is predicted by these variables, the relation is actually the opposite direction. That is, when these variables are elevated, HYNEIO is already treading down.

6.2 Discussion

We have documented thus far strong evidence that HYNEIO is able to predict a battery of credit and business cycle variables in addition to market prices and monetary policies. A natural question that follows is what is special about this specific component of investor flows. On the one hand, given well-documented evidence that mutual fund investors respond to past fund performance (e.g., Ippolito 1992, Chevalier and Ellison 1997, and Sirri and Tufano 1998 among others) and the dumb money literature (e.g., Frazzini and Lamont 2008, and Lou 2012 among others) which thus suggests that mutual fund investors are not likely to be informed, our results might seem contradictory to common perception in academic literatures. On the other hand, there is growing literature which suggests that individual investors can be informed or sophisticated (e.g., Keniel, Saar and Titman 2008, Kelley and Tetlcok 2013).

The following institutional features of HYNEIO set it apart from the usual net fund flow measures and also help reconcile our findings with the common perception in the literature. First, within-family flow shifts, which net-exchanges (i.e., NEIO) measure, are subject to much less transaction costs compared with the total net flows. Many fund families charge less fees when moving money across funds within the same family. Thus, investors' shifts in their beliefs about future economic outcomes will be reflected in within-family flow shifts much earlier and in a cleaner way than in total net flows; given that this is money that is already invested in the same fund family. As a result, this is a clear measure of changes in investor beliefs. Furthermore, net sales, which accounts for the major portion of total net flows, are subject to periodic flows into retirement accounts, which makes net flows a much noisier measure of future outlook.[15]

Now, the fact that exchanges are cleaner doesn't have to be associated with smart money. In particular, Ben-Rephael, Kandel and Wohl (2012) find that equity exchanges capture excessive change in demand which is followed by a reversal. This leads us to the second feature of HYNEIO, which is that the investor clientele in high-yield bond mutual funds is quite different from the investor base in stock or investment-grade bond funds. Typical employment retirement plans do not offer many (if at all) high-yield bond investment selections in their menu (also less index funds available for high yield funds). Investing in high yield bond funds thus require being active and doing research on the part of investors, thus leading to the separation of investor pools in high-yield funds versus other asset categories, e.g., equity and investment-grade bonds. From our detailed conversations with the ICI representatives, they also confirm that investor pools are quite different and relatively higher concentration of wealthy and active investors in high-yield bond funds.

In sum, our view is that HYNEIO is an early indicator because it reflects an early shift in taste (or demand) by relatively more sophisticated investors. The ability of HYNEIO to positively predict both stock and bond market returns confirms this notion.

[15]ICI provides information regarding money invested in mutual funds by defined contribution and IRA pension plans. In particular, around 52% of equity mutual fund assets are held by these plans. Investment grade corporate bonds and balanced funds present similar ratios.

7. Conclusion

The literature on credit and business cycles is voluminous, where numerous studies explore what predicts these cycles (e.g., Gilchrist and Zakrajšek 2012 and López-Salido, Stein, and Zakrajšek 2015). Recently, the focused has started to shift towards exploring the role of investor demand in driving fluctuations in credit markets and future economic activities.

In this paper we add to this growing literature by offering a direct predictor of investor demand for credit and show that this measure can serve as a leading indicator for both credit and business cycles.

Our measure captures investors' asset allocation decisions toward high-yield bonds, using shifts of money which is already invested across asset classes within a fund family. We show that this measure predicts up to 12 months in advance, all alternative flow components across different asset classes, and is able to capture early shocks in investor demand. As such, this measure is able to predict a battery of credit and business cycle variables that have close links to economic activities.

It particular, we find that our measure positively predicts a battery of credit cycle variables. It predicts growth in financial intermediaries' balance sheets and net amounts of total bond issuance. In addition, it is able to predict a year in advance an increase in the share of low quality bond issuers (Greenwood and Hanson 2013) and the degrees of reaching for yield in the bond market (Becker and Ivashina 2015).

Linking our measure to the business cycle, we find that our measure is able to predict various credit spreads such as the high-yield, the default credit spreads and Gilchrist and Zaerajsek's (2012) excess bond premium (EBP); and can also predict future changes in monetary policies. Consistent with that, our measure is able to positively (negatively) predict GDP growth (unemployment rates) earlier than the EBP or credit spreads.

The fact that all of our tests show that our measure is an early predictor, provides robust evidence that shocks in investors demand can serve as an early signal for credit and business cycles, and should take into consideration by policy makers.

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Table 1. Summary Stat and Correlation Matrices of Main Asset Classes' Flow Components

This table reports summary statistics and correlation matrices for *NEIO* and *NSR* flow components in the following asset classes: high-yield corporate bond mutual funds (*HY*); investment grade corporate bond mutual funds (*IG*); equity mutual funds (*EQ*); and Government and Money Market mutual funds (*GM*). The data is obtained from ICI from February 1984 to December 2012. The HY, IG, EQ and GM asset classes are constructed using ICI's categories 22, 10-17, 1-9, and 27-33 respectively (see Appendix A for more details). For each asset class, *NEIO* and *NSR* are the net sales (sales minus redemptions) and net exchanges (exchanges-in minus exchanges-out) normalized by the end-of-previous month assets. Panel A reports the average, average of the absolute value and standard deviation, of each asset class flow component. Panel B.1 reports the correlations between NEIO and NSR *within* each asset class. Panels B.2.1 (B.2.2) reports the correlations between NEIOs (NSRs) *across* asset classes.

Panel A – Summary Statistics

Variables	Ave	Ave-Abs	SD
HY NEIO	0.006	0.510	0.710
EQ NEIO	-0.048	0.224	0.282
IG NEIO	-0.020	0.142	0.192
GM NEIO	0.038	0.189	0.289
HY NSR	0.696	1.170	1.397
EQ NSR	0.522	0.626	0.630
IG NSR	0.878	0.962	0.936
GM NSR	0.421	1.564	1.964

Panel B – Correlation Matrices

B.1 NEIO and NSR within Groups

	NSR			
NEIO	HY	EQ	IG	GM
HY	0.51			
EQ		0.37		
IG			0.36	
GM				0.02

B.2.1 NEIO across Groups

	NEIO		
NEIO	EQ	IG	GM
HY	0.34	0.36	-0.60
EQ		0.22	-0.77
IG			-0.42

B.2.2 NSR across Groups

	NSR		
NSR	EQ	IG	GM
HY	0.36	0.50	0.12
EQ		0.65	0.07
IG			0.04

Table 2. Regressions of Future High-Yield-Share and Reaching-for-Yield on *HYNEIO*

This table presents results of quarterly predictive time series regressions of high-yield-share ("*LnHYS*") and reaching for yield ("*RFY*") on *HYNEIO* and other explanatory variables. *LnHYS* (Specifications 1-3) is the natural logarithm of the high-yield-share, which is defined as the dollar fraction of non-financial debt issues receive a high yield rating, based on data from the Fixed Income Securities Database (FISD). *RFY* (Specifications 4-6) is defined for each rating category *j*, as the ratio of value-weighted average yield of all corporate bonds with rating *j* to equal-weighted average yield of the same corporate bonds, $RFY_{jt} = \Sigma \mathrm{w}_{\mathrm{jt}} y_{jt} / \Sigma \frac{1}{\mathrm{n}} y_{jt}$, where the weight w_{jt} is determined by amounts outstanding of bonds. We then take the average across rating categories. The data is obtained from the Fixed Income Securities Database (FISD). *HYNEIO* is net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012.

The regressions take the following form: $DEP_{q+1:q+4} = a + \beta * HYNEIO_{q-3:q} + \gamma * DEP_{q-3:q} + Controls + \varepsilon_{q+4}$, where the dependent variable (*LnHYS* or *RFY*) is calculated over a period of 4 quarters. In all specifications, *HYNEIO* and the lag of the dependent variable (DEP) are calculated over the previous 4 quarters. In addition, we control for the term spread (*TS*), calculated as the difference between long-term and short-term government bonds; the default spread (*DS*) calculated as the difference between BAA and AAA corporate bond index; short rate, which is the 3 months T-Bill rate (*TB*); the dividend yield (*DY*) calculated using CRSP as the sum of all dividends divided by the market cap. Other controls are lagged *LnHYS* over the previous 4 quarters (*RFY* regressions); the high-yield bond index excess return during the previous 4 quarters (*HYRET*); and for Gilchrist and Zakrajšek (2012) excess bond premium (EBP), which is the difference between total corporate bond spread and the spread component that is predicted by expected defaults. *EPB* data is available until September 2010. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

	LnHYS q+1:q+4			*RFY q+1:q+4*		
	(1)	(2)	(3)	(4)	(5)	(6)
HYNEIO q-3:q	0.089	0.087	0.096	0.022	0.022	0.019
	3.99	4.20	4.09	4.29	4.42	4.01
DEP q-3:q	0.203	0.106	0.075	-0.272	-0.327	-0.314
	1.99	0.95	0.64	2.33	2.96	2.83
TS q	0.579	-3.348	-3.313	-4.186	-3.585	-2.654
	0.06	0.32	0.31	2.21	1.64	1.22
DS q	-19.027	7.416	4.900	-13.981	-16.100	-13.084
	1.08	0.28	0.20	2.90	3.10	3.20
TB q	-10.863	-13.275	-14.324	-1.920	-1.302	-0.622
	2.25	2.16	2.30	2.15	1.01	0.56
DY q	-3.368	-2.804	-1.141	18.030	19.526	18.605
	0.24	0.18	0.07	2.57	2.83	2.81
LnHYS q-3:q					0.046	0.056
					1.73	1.86
EBP q		-0.369	-0.428		0.041	0.031
		2.22	2.31		1.52	1.31
HYRET q-3:q			-0.008			0.004
			1.55			1.58
AdjRSQ	0.602	0.641	0.644	0.582	0.606	0.617

Table 3. Regression of Future Credit Spreads and EBP

This table presents results of quarterly predictive time series regressions of credit spreads and Gilchrist and Zakrajšek's (2012) excess bond premium (EBP) on *HYNEIO* and other explanatory variables. *HYNEIO* is the net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012. Panel A, reports the regressions of the high-yield spread (HY-Aaa, Specifications 1-4) and the default spread (Baa-Aaa, Specifications 5-8). The regressions take the following form: $Spread_{q+4} = a + \beta * HYNEIO_{q-3:q} + \gamma * Spread_q + Controls + \varepsilon_{q+4}$, where dependent variable is either *HY-AAA* or *Baa-Aaa* at end-of-quarter *q*+4. *HYNEIO* $_{q-3:q}$ is calculated over the previous 4 quarters and *Spread q* is the relevant credit spread at end-of-quarter *q*. Panel B reports the regressions of Gilchrist and Zakrajšek's (2012) excess bond premium (EBP), which is the difference between total corporate bond spread and the spread component that is predicted by expected defaults. *EPB* data is available until September 2010. Following Gilchrist and Zakrajšek, the regressions take the following form: $AveEBP_{q+1} = a + \beta * HYNEIO_q + \gamma * AveEBP_q + Controls + \varepsilon_{q+1}$, where $AveEBP_{q+1}$ ($AveEBP_q$) is the average monthly spread over quarter *q*+1 (*q*). Other control variables are defined in Table 2. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

Panel A – HY-Aaa and Baa-Aaa Credit Spreads on HYNEIO

	Spread q+4							
	HY-Aaa				*Baa-Aaa*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	-0.2456	-0.1739	-0.2162	-0.2264	-0.0197	-0.0171	-0.0155	-0.0259
	3.06	2.51	2.71	2.50	1.91	1.69	1.90	2.40
Spread q	0.198	0.221	-0.101	-0.092	0.332	0.358	0.151	0.187
	1.45	1.81	0.36	0.34	2.47	1.91	0.54	0.73
TS q		-37.446	-52.819	-53.659		-3.681	-4.636	-5.502
		0.92	1.07	1.06		0.71	0.53	0.64
TB q		14.415	10.100	10.741		-0.748	-1.297	-0.600
		0.86	0.42	0.45		0.21	0.22	0.10
DY q		1.323	24.416	22.993		-1.493	4.352	2.433
		0.03	0.45	0.43		0.23	0.39	0.22
LnHYS q-3:q			0.394	0.406			0.126	0.125
			1.01	1.06			1.29	1.29
EBP q			2.079	2.127			0.293	0.338
			2.12	2.07			2.02	2.21
HYRET q-3:q				0.006				0.006
				0.33				1.81
AdjRSQ	0.195	0.257	0.363	0.356	0.121	0.107	0.185	0.190

Panel B – AveEBP on HYNEIO

	AveEBP q+1		
	(1)	(2)	(3)
HYNEIO q	-0.0404	-0.0380	-0.0381
	2.19	2.05	2.07
AveEBP q	0.8356	0.8018	0.7991
	9.38	8.71	8.10
TS q		-0.125	-0.223
		0.05	0.08
DS q		7.550	7.551
		0.71	0.71
TB q		2.019	1.950
		1.36	1.16
LnHYS q-3:q			-0.005
			0.12
AdjRSQ	0.705	0.703	0.700

Table 4. Regressions of Future Growth in Intermediary Balance Sheets and Net Bond Issuance on *HYNEIO*

This table presents results of quarterly predictive time series regressions of growth in intermediary balance sheet assets ("*dA/A")* and net bond issuance ("*NBI"*) on *HYNEIO* and other explanatory variables. *dA/A* is a difference in balance sheet assets between end of the quarter and end of the previous quarter divided by the assets at the end of the previous quarter. Intermediaries' balance sheet data is obtained from Table L.129 of the Federal Reserve Flow of Funds (Etula and Muir, 2014). *NBI* is defined as total amounts of bond issuance by nonfinancial corporate business during a given quarter out of total bond amounts outstanding in previous quarter, available in the flow of funds data. *HYNEIO* is net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012. The regressions take the following form: $DEP_{q+1} = a + \beta * HYNEIO_{q-3:q} + \gamma * DEP_{q-3:q} + Controls + \varepsilon_{q+1}$, where the dependent variable (*dA/A* or *NBI*) is calculated over subsequent quarter. *HYNEIO* and the lag of the dependent variable are calculated over the previous 4 quarters. Other control variables are defined in Table 2. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

	dA/A q+1			*NBI q+1*		
	(1)	(2)	(3)	(4)	(5)	(6)
HYNEIO q-3:q	0.003	0.003	0.003	0.001	0.001	0.001
	2.40	2.13	2.14	2.15	2.09	1.89
DEP q-3:q	-0.007	0.013	0.011	0.604	0.522	0.527
	0.21	0.37	0.34	5.23	3.79	3.75
TS q	1.205	1.549	1.543	-0.046	0.165	0.162
	1.61	1.76	1.77	0.27	0.90	0.87
DS q	-2.045	1.705	1.730	0.796	0.956	0.946
	1.20	0.90	0.90	2.35	1.63	1.59
TB q	0.914	1.284	1.296	0.158	0.328	0.321
	2.61	2.53	2.42	1.60	2.41	2.09
DY q	-0.083	-1.389	-1.409	-0.066	-0.336	-0.329
	0.10	1.41	1.33	0.24	1.03	0.97
LnHYS q-3:q		-0.016	-0.016		0.000	-0.001
		1.38	1.41		0.18	0.21
EBP q		-0.040	-0.039		0.001	0.000
		2.09	2.02		0.20	0.12
HYRET q-3:q			0.000			0.000
			0.11			0.16
AdjRSQ	0.106	0.142	0.133	0.488	0.501	0.496

Table 5. Regressions of Future Changes in Real GDP and Unemployment Rate on *HYNEIO*

This table presents results of quarterly predictive time series regressions of changes in real GDP (*DiffLnRealGDP)* changes in unemployment rates (*DiffUER)* on *HYNEIO* and other explanatory variables. *HYNEIO* is the net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012. In Panel A, we explore the relation between *DiffLnRealGDP* and *HYNEIO* over a period of 4 quarters (Specifications 1-4) and 8 quarters (Specifications 5-8). The regressions take the following form: $DiffLnRealGDP_{q+1:q+j} = a + \beta * HYNEIO_{q-3:q} + \gamma * DiffLnRealGDP_{q-3:q} + Controls + \varepsilon_{q+4}$, where $DiffLnRealGDP_{q+1:q+j}$ is a difference in log real GDP from end-of-quarter *q* to end-of-quarter *q+4* or *q+8*, and $DiffLnRealGDP_{q-3:q}$ is a difference in log real GDP from end-of-quarter *q-4* to end-of-quarter *q*. In a similar manner, $HYNEIO_{q-3:q}$ is calculated over the previous 4 quarters. In Panel B, we explore the relation between *DiffUER* and *HYNEIO* over a period of 4 quarters (Specifications 1-4) and 8 quarters (Specifications 5-8). The regressions take the following form: $DiffUER_{q+1:q+j} = a + \beta * HYNEIO_{q-3:q} + \gamma * DiffUER_{q-3:q} + Controls + \varepsilon_{q+4}$, where $DiffUER_{q+1:q+j}$ is the difference between the unemployment rate at the end-of-quarter *q*+4 or *q*+8 and end-of-quarter *q*. $DiffUER_{q-3:q}$ is the difference between the unemployment rate at the end-of-quarter *q* and end-of-quarter *q*-4. $HYNEIO_{q-3:q}$ is calculated over the previous 4 quarters. Other control variables are defined in Table 2. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

Panel A – Changes in Real GDP on *HYNEIO*

	DiffLnRealGDP							
	q+1:q+4				*q+1:q+8*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	0.002	0.002	0.002	0.002	0.003	0.002	0.002	0.003
	3.45	2.93	2.74	2.54	3.05	2.01	2.02	2.06
DiffLnRealGDP q-3:q	0.371	0.219	0.185	0.181	0.518	0.381	0.248	0.237
	2.99	1.70	1.13	1.07	2.46	1.75	0.88	0.81
TS q		0.427	0.560	0.584		1.467	1.899	1.966
		2.34	2.01	2.04		2.65	2.80	2.83
DS q		-0.738	0.390	0.299		-0.234	0.491	0.236
		1.87	0.50	0.40		0.30	0.37	0.18
TB q		0.187	0.311	0.297		0.512	0.823	0.785
		1.89	1.38	1.29		2.78	2.49	2.36
DY q		-0.179	-0.481	-0.438		-0.778	-1.326	-1.205
		0.57	1.25	1.14		1.42	2.00	1.83
LnHYS q-3:q			-0.002	-0.002			0.001	0.001
			0.33	0.32			0.13	0.16
EBP q			-0.012	-0.013			-0.008	-0.011
			1.91	1.93			1.00	1.18
HYRET q-3:q				0.000				0.000
				0.94				1.53
AdjRSQ	0.293	0.327	0.378	0.375	0.208	0.333	0.349	0.353

Panel B – Changes in Unemployment Rate on *HYNEIO*

	DiffUER							
	q+1:q+4				*q+1:q+8*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	-0.143	-0.113	-0.089	-0.071	-0.258	-0.182	-0.147	-0.118
	4.14	4.13	4.66	3.75	4.67	3.60	3.74	2.79
DiffUER q-3:q	0.456	0.426	0.286	0.305	0.399	0.588	0.292	0.324
	4.06	2.98	1.86	1.98	2.88	3.47	1.90	2.01
TS q		-15.062	-27.631	-25.756		-58.351	-87.911	-84.796
		1.61	2.48	2.28		2.19	2.73	2.67
DS q		67.254	-1.915	-10.238		4.606	-4.973	-18.808
		1.64	0.09	0.40		1.03	0.12	0.41
TB q		8.800	-4.533	-5.355		12.675	-14.360	-15.727
		1.39	0.59	0.65		1.06	0.97	1.05
DY q		-22.399	-2.699	0.992		-29.339	7.737	13.871
		1.18	0.16	0.05		1.00	0.30	0.51
LnHYS q-3:q			-0.055	-0.038			-0.165	-0.137
			0.33	0.22			0.54	0.43
EBP q			0.770	0.689			0.607	0.473
			2.12	1.97			1.41	1.07
HYRET q-3:q				-0.010				-0.017
				1.12				1.29
AdjRSQ	0.360	0.448	0.512	0.515	0.259	0.473	0.466	0.468

Table 6. Regressions of Future Changes in Monetary Policy on *HYNEIO*

This table presents results of quarterly predictive time series regressions of changes in monetary policy on *HYNEIO* and other explanatory variables. Changes in monetary policy are measured using the changes in the federal discount rate (Specifications 1-6) and Romer & Romer (2004) monetary policy shocks measure (Specifications 7-10). Given the nature of changes in monetary policy, we focus on a 2-year horizon where we sum the changes during the period. To explore *HYNEIO*'s timing, we also skip one year in Specifications 4-6 and 9-10. *HYNEIO* is the net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012. The regressions take the following form: $DEP_{q+j:q+k} = a + \beta * HYNEIO_{q-3:q} + \gamma * DEP_{q-3:q} + Controls + \varepsilon_{q+k}$, where $DEP_{q+j:q+k}$ is one of the two monetary policy measures during the specified time interval. Other control variables are defined in Tables 2. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

	Discount Rate Change						*Romer &Romer*			
	q+1:q+8			*q+5:q+12*			*q+1:q+8*		*q+5:q+12*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HYNEIO q-3:q	0.198	0.193	0.194	0.170	0.207	0.217	0.071	0.054	0.113	0.098
	3.42	3.27	3.15	2.76	2.33	2.27	2.13	1.89	2.94	2.35
DEP q-3:q	7.078	4.551	1.657	-4.182	-1.640	-3.445	0.997	-2.578	2.333	4.352
	2.96	1.39	0.44	1.75	0.59	1.24	0.43	1.44	1.14	2.01
TS q	114.108	118.809	71.955	98.752	113.835	103.499	-18.597	-5.597	26.421	29.169
	2.50	1.85	1.11	2.92	2.93	2.78	0.73	0.33	1.07	1.29
DS q	-6.910	-88.143	-53.435	-65.622	-117.742	-76.062	-202.176	-169.254	-8.754	-65.560
	0.08	1.08	0.64	0.95	1.28	0.80	2.53	3.07	0.13	0.87
TB q	-12.554	-25.350	-58.345	-6.714	-8.687	-16.997	-61.473	-46.052	-30.078	-29.748
	0.64	0.90	2.01	0.38	0.32	0.58	3.70	4.02	2.05	1.98
DY q	-6.442	83.799	114.990	-13.589	-22.242	-31.760	203.068	213.088	118.587	113.321
	0.12	1.64	2.40	0.23	0.32	0.54	4.77	6.84	2.81	2.82
LnHYS q-3:q		1.778	1.214		-0.104	-0.450		0.722		-0.078
		3.78	2.56		0.25	0.81		2.74		0.28
EBP q		0.026	-0.168		0.905	0.827		-0.328		0.503
		0.05	0.28		1.32	1.13		1.45		1.38
HYRET q-3:q		-0.045	-0.038		0.000	0.009		-0.010		0.025
		2.48	2.09		0.01	0.39		1.32		1.26
DiffLnGDP q-3:q			26.268			-17.731		-18.981		-7.630
			1.08			0.76		1.98		0.41
DiffUER q-3:q			26.268			-0.853		-0.387		0.249
			0.72			2.30		2.62		0.79
AdjRSQ	0.447	0.619	0.642	0.546	0.560	0.579	0.697	0.822	0.679	0.719

Table 7. Regression of Future Stock Market Return on *HYNEIO*

This table presents results of quarterly predictive time series regressions of excess stock market return on *HYNEIO* and other explanatory variables. *HYNEIO* is the net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012. In particular, we contrast *HYNEIO* with *EQNEIO* when we predict the stock market return; where *EQNEIO* is the net exchanges (exchanges-in minus exchanges-out) of the equity category, normalized by the end-of-previous month assets (see Appendix A for more details). The regressions take the following form: $ExMkt_{q+1:q+4} = a + \beta * EQNEIO_{q-3:q} + \gamma * HYNEIO_{q-3:q} + Controls + \varepsilon_{q+4}$, where $ExMkt_{q+1:q+4}$ is the future excess market return over subsequent 4 quarters. $ExRET_{q-3:q}$ ($HYRET_{q-3:q}$) is the cumulative excess return of the market index (Barclay's high-yield bond index) over the previous 4 quarters. Other control variables are defined in Table 2. "*1 SD*" is the 1 standard deviation effect of *HYNEIO* on returns. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

	MktExRet q+1:q+4					
	(1)	(2)	(3)	(4)	(5)	(6)
EQNEIO q-3:q	-0.0072		-0.0129	0.0136		0.0188
	0.40		0.71	0.58		0.91
HYNEIO q-3:q		0.0184	0.0192	0.0176	0.0206	0.0193
		2.16	2.28	2.37	2.54	2.43
MktExRet q-3:q	-0.05588	-0.13206	-0.09478	-0.09487	-0.29329	-0.33960
	0.41	1.19	0.72	0.70	1.95	1.98
HYRET q-3:q	0.00284	-0.00028	-0.00060	-0.00099	-0.00495	-0.00407
	1.31	0.17	0.36	0.62	2.16	2.05
TS q				-2.922	0.506	0.218
				1.14	0.12	0.06
DS q				-3.000	11.675	14.471
				0.48	1.35	1.59
TB q				-2.349	-0.017	0.324
				1.34	0.01	0.11
DY q				11.63	6.90	7.86
				1.94	1.22	1.39
LnHYS q-3:q					0.003	0.005
					0.08	0.16
EBP q					-0.224	-0.227
					3.45	3.47
1 SD		5.88	6.14	5.62	6.58	6.15
AdjRSQ	0.001	0.078	0.078	0.147	0.328	0.331

Table 8. Regression of Bond Market Index Returns on *HYNEIO*

This table presents results of quarterly predictive time series regressions of bond market index returns on *HYNEIO* and other explanatory variables. For comparison, we also present results for *HYNSR*. *HYNEIO* and *HYNSR* are the net sales (sales minus redemptions) and net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012. Bond index returns for various rating categories are obtained from Barclays and are net of the 3 month T-Bill returns. In particular, we present results for average investment grade (*IG*) bond returns, calculated as the equally average of AAA, AA, A and Baa; and for HY bond returns. The regressions take the following form: $R^e_{q+1:q+k} = a + \beta * FLOW_{q-3:q} + c_1 * TS_q + c_2 * DS_q + c_3 * TB_q + c_4 * DY_q + c_5 * R^e_{q-3:q} + \varepsilon_{q+k}$, where $R^e_{m+1:m+k}$ is the relevant bond index excess return for different horizons. *FLOW* is *HYNEIO* or *HYNSR* based on the previous 12 months information. HYRET and AveIGRET are the relevant bond index excess return during the previous 12 months ($R^e_{q-3:q}$). Other control variables are defined in Tables 2. "*1 SD*" is the 1 standard deviation effect of *HYNEIO* and *HYNSR* on returns. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the monthly overlapping period. *t*-statistics are reported below the coefficient estimates.

	HYNEIO					HYNSR				
	Q1-Q1	Q1-Q2	Q1-Q4	Q1-Q8	Q1-Q12	Q1-Q1	Q1-Q2	Q1-Q4	Q1-Q8	Q1-Q12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HY Bond Returns										
FLOW	0.317	0.501	0.283	-0.454	-0.812	-0.012	-0.060	-0.191	-0.371	-0.646
	2.10	1.95	0.55	0.41	0.90	0.25	0.77	1.82	2.09	3.70
HYRET	-0.014	-0.065	-0.125	-0.238	-0.173	0.043	0.059	0.021	0.021	-0.025
	0.33	0.93	1.30	1.32	0.60	0.98	0.85	0.27	0.27	0.12
1 SD	1.05	1.66	0.94	-1.50	-2.69	-0.15	-0.79	-2.51	-4.88	-8.51
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AdjRSQ	0.150	0.272	0.426	0.549	0.410	0.125	0.249	0.450	0.597	0.539
Average IG Bond Returns										
FLOW	0.129	0.196	0.047	-0.761	-0.820	-0.013	-0.043	-0.153	-0.300	-0.352
	1.81	1.77	0.23	2.41	2.14	0.58	1.14	3.19	4.48	4.36
AveIGRET	-0.059	-0.089	-0.158	0.027	-0.008	-0.009	0.010	-0.010	0.105	0.106
	1.69	1.46	1.79	0.22	0.05	0.23	0.17	0.10	1.00	0.73
1 SD	0.43	0.65	0.16	-2.52	-2.71	-0.18	-0.57	-2.01	-3.95	-4.63
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AdjRSQ	0.105	0.215	0.410	0.317	0.240	0.094	0.213	0.471	0.431	0.353

Table 9. Lead-Lag Relations among Flow Components of Various Asset Classes

This table presents results of quarterly lead-lag regressions between *NEIO* and *NSR* flow components in the following asset classes: high-yield corporate bond mutual funds (*HY*); investment grade corporate bond mutual funds (*IG*); equity mutual funds (*EQ*); and Government and Money Market mutual funds (*GM*). The data is obtained from ICI from February 1984 to December 2012 (see Appendix A for more details). For each asset class, *NEIO* and *NSR* are the net sales (sales minus redemptions) and net exchanges (exchanges-in minus exchanges-out) normalized by the end-of-previous month assets. Panel A, B and C report the lead-lag relation between the HY and IG categories, HY and EQ categories and HY and G M categories, respectively. In all specifications, the independent variables are calculated based on previous 12 month information at quarterly frequency. The dependent variables are calculated based on subsequent 2 quarters (*q*+1:*q*+2 in Specifications 1-4) and 4 quarters (*q*+1:*q*+4 in Specifications 5-8). In a similar manner, *HYNEIO* q-3:q is the sum of monthly *NEIO* in the *HY* category over the previous 4 quarters. *HYRETq-3:q*, *BaaRETq-3:q*, and *EXRETq-3:q* are the cumulative excess return on Barclay's high-yield bond index, *Baa* bond index, and excess market index over the previous 4 quarters, respectively. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates. Given the persistence in the NSR components, the coefficient estimates and standard errors are corrected using Amihud and Hurvich (2004) correction procedure.

Panel A – HY and IG Categories

	q+1:q+2				*q+1:q+4*			
	HYNEIO	*HYNSR*	*IGNEIO*	*IGNSR*	*HYNEIO*	*HYNSR*	*IGNEIO*	*IGNSR*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	0.248	1.034	0.121	0.932	0.327	2.077	0.232	2.112
	3.23	5.56	2.67	3.91	2.00	4.96	2.73	3.80
HYNSR q-3:q	-0.023	0.297	-0.026	-0.072	-0.108	0.320	-0.062	-0.232
	0.73	4.04	1.77	0.89	1.73	2.09	1.91	1.21
IGNEIO q-3:q	-0.364	-1.237	0.186	-0.352	-0.794	-3.341	0.194	-0.232
	1.38	2.51	2.21	1.00	1.47	-2.51	0.96	1.57
IGNSR q-3:q	0.083	0.273	0.021	0.474	0.216	0.700	0.047	0.923
	1.39	2.47	1.31	4.83	1.57	2.59	1.12	3.83
HYRET q-3:q	-0.028	-0.356	-0.011	-0.177	-0.036	-0.660	-0.016	-0.416
	0.80	3.24	0.79	3.52	0.55	2.66	0.65	3.14
BAARET q-3:q	0.041	0.445	0.025	0.346	0.066	0.858	0.040	0.755
	0.84	2.39	1.00	3.73	0.74	1.91	0.93	2.87
AdjRSQ	0.081	0.578	0.273	0.608	0.150	0.489	0.313	0.530

Panel B – HY and Equity Categories

	q+1:q+2				q+1:q+4			
	HYNEIO	*HYNSR*	*EQNEIO*	*EQNSR*	*HYNEIO*	*HYNSR*	*EQNEIO*	*EQNSR*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	0.136	0.714	0.125	0.495	0.036	1.259	0.263	1.230
	1.51	3.63	4.61	3.33	0.17	2.58	4.01	3.97
HYNSR q-3:q	-0.013	0.373	-0.025	-0.024	-0.045	0.564	-0.059	-0.102
	0.50	2.95	2.71	0.69	0.82	2.52	4.03	1.31
EQNEIO q-3:q	0.083	-0.075	0.218	-0.314	0.304	-0.067	0.334	-1.186
	0.24	0.09	2.44	0.91	0.43	0.03	1.72	1.37
EQNSR q-3:q	0.041	0.043	0.037	0.406	0.134	0.200	0.074	0.794
	0.55	0.26	2.34	3.88	0.96	0.53	1.62	3.91
HYRET q-3:q	0.036	-0.070	-0.002	-0.038	0.031	-0.094	-0.006	-0.093
	1.28	1.10	0.26	1.23	1.19	0.63	0.42	1.61
EXRET q-3:q	-6.002	-9.452	-0.045	3.574	-10.464	-16.011	-0.308	6.668
	2.51	1.81	0.07	1.39	2.29	1.40	0.33	1.39
AdjRSQ	0.161	0.508	0.288	0.619	0.239	0.376	0.506	0.576

Panel C – HY and Government and Money-Market Categories

	q+1:q+2				q+1:q+4			
	HYNEIO	*HYNSR*	*GMNEIO*	*GMNSR*	*HYNEIO*	*HYNSR*	*GMNEIO*	*GMNSR*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	0.128	0.640	-0.115	0.207	-0.074	0.911	-0.206	0.216
	1.51	3.38	3.25	0.72	0.34	2.17	3.27	0.43
HYNSR q-3:q	0.004	0.395	0.019	-0.043	-0.006	0.402	0.041	-0.176
	0.14	3.90	2.59	0.54	0.11	2.72	2.62	1.19
GMNEIO q-3:q	0.194	-0.226	0.148	-0.954	0.007	-0.810	0.251	-1.479
	0.93	0.58	1.79	1.61	0.02	0.92	1.74	1.52
GMNSR q-3:q	-0.004	0.035	0.010	0.258	0.029	0.174	0.043	0.433
	0.12	0.49	0.71	2.26	0.44	1.07	1.81	2.87
HYRET q-3:q	-0.001	-0.110	0.000	-0.097	0.032	-0.105	0.016	0.024
	0.02	1.54	0.06	1.47	0.60	0.72	1.22	0.18
T-bill q	-9.012	22.654	-2.164	125.481	-28.953	37.969	-7.147	275.547
	0.45	0.52	0.54	4.93	0.80	0.37	0.97	4.47
AdjRSQ	0.048	0.493	0.250	0.406	0.043	0.378	0.427	0.540

Table 10. *HYNEIO* and other Asset Class *NEIO*s

In this table we extend our previous analyses by decomposing *HYEIO* to its potential sources (Panel A), and exploring the relation between *HYNEIO* and other asset class *NEIO*s (Panel B). In Panel A, we decompose HYNEIO to its potential resources. We take advantage of the fact that by construction, investor exchanges in and out of each asset classes should sum up to zero. Thus, we rewrite HYNEIO as

$$-\frac{\left[EQ\ Net\ Exchanges + IG\ Net\ Exchanges + GM\ \ Net\ Exchanges + Other\ Net\ Exchanges\right]}{LagHY\,Assets}$$

= EQC+IGC+GMC+OC

where the suffix "C" stands for the relevant component. Using this decomposition, we examine where the predicting power of *HYNEIO* is coming from. The regressions take the following form:

$$DEP_{q+j:q+k} = a + \beta_1 * EQC_{q-3:q} + \beta_2 * IGC_{q-3:q} + \beta_3 * GMC_{q-3:q} + \beta_4 * OC_{q-3:q}$$
$$+\gamma * DEP_{q-3:q} + Controls + \varepsilon_{q+k}$$

In Panel B we include *EQNEIO* (equity), *IGNEIO* (investment grade) and *GMNEIO* (government and money market) in our regressions (see Table 1 for asset class definitions).

Other control variables are defined in Tables 2 and are not presented for brevity. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

Panel A – Decomposing *HYNEIO*

	LnHYS	*RFY*	*NBI*	*DA/A*	*HY-Aaa*	*MktExRet*	*GDP1Y*	*UER1Y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EQC q-3:q	0.0944	0.0185	0.0006	0.0024	-0.1725	0.0236	0.0023	-0.0696
	4.21	3.90	1.42	1.88	2.51	2.95	3.89	3.18
IGC q-3:q	0.1147	0.0143	0.0003	0.0043	-0.3001	0.0406	0.0031	-0.1067
	4.96	3.22	1.70	3.35	3.25	2.48	3.15	2.31
GMC q-3:q	0.0933	0.0178	0.0007	0.0023	-0.1953	0.0224	0.0021	-0.0677
	4.13	3.64	1.93	1.65	2.68	2.09	3.73	2.97
OC q-3:q	0.0986	0.0187	0.0009	0.0018	-0.1653	0.0136	0.0022	-0.0638
	4.02	3.57	0.70	1.05	1.93	1.81	3.08	2.58
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Panel B – Contrasting *HYNEIO* with other asset class *NEIO*s

	LnHYS	*RFY*	*NBI*	*DA/A*	*HY-Aaa*	*MktExRet*	*GDP1Y*	*UER1Y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	0.1032	0.0185	0.0009	0.0026	-0.1731	0.0205	0.0024	-0.0765
	4.06	3.87	1.98	2.08	2.61	2.37	3.87	3.09
EQNEIO q-3:q	0.0337	-0.0072	0.0028	-0.0104	-0.3910	-0.0377	-0.0012	0.0556
	0.62	0.43	1.43	1.58	1.81	1.38	0.55	0.57
IGNEIO q-3:q	-0.1365	0.0076	0.0010	-0.0094	0.4326	-0.0235	-0.0028	0.0942
	2.11	0.56	0.95	2.47	1.83	0.85	1.18	0.73
GMNEIO q-3:q	0.0050	-0.0090	0.0017	-0.0113	0.1420	-0.0391	0.0006	0.0302
	0.06	0.44	0.86	1.74	0.51	1.14	0.17	0.20
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Table 11. *HYNEIO* and Asset Class *NSR*s

In this table we extend our previous analyses by exploring the relation between *HYNEIO* and *HYNSR* (Panel A) and *HYNEIO* and other asset class *NSRs* (Panel B). Other control variables are defined in Tables 2 and are not presented for brevity. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates. Given the persistence in the NSR components, the coefficient estimates and standard errors are corrected using Amihud and Hurvich (2004) correction procedure.

Panel A – HYNEIO and HYNSR

	LnHYS	*RFY*	*NBI*	*dA/A*	*HY-AAA*	*MktExRet*	*GDP1Y*	*UER1Y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	0.107	0.019	0.001	0.003	-0.1540	0.0169	0.0019	-0.0449
	4.06	4.12	1.86	1.91	2.11	2.66	2.07	1.66
HYNSR q-3:q	0.002	0.000	0.000	0.000	-0.028	0.002	0.0006	-0.0328
	0.31	0.08	0.53	0.39	1.39	0.37	2.56	3.85
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Panel B – HYNEIO and other Asset Class NSRs

	LnHYS	*RFY*	*NBI*	*dA/A*	*HY-AAA*	*MktExRet*	*GDP1Y*	*UER1Y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HYNEIO q-3:q	0.124	0.017	0.001	0.003	-0.323	0.0219	0.0029	-0.1043
	4.89	3.12	1.81	2.03	3.12	2.27	3.54	2.73
EQNSR q-3:q	0.023	-0.001	0.000	-0.001	-0.174	0.007	0.0010	-0.0283
	1.46	-0.38	0.33	-0.54	2.18	0.89	1.28	1.09
IGNSR q-3:q	-0.009	0.002	0.000	0.001	-0.031	-0.003	0.0000	-0.0225
	1.27	0.64	0.47	0.78	0.73	0.69	0.11	1.49
GMNSR q-3:q	-0.018	0.001	0.000	0.000	0.109	-0.006	-0.0009	0.0519
	2.58	0.63	-0.42	-0.81	1.61	1.73	1.49	1.78
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Table 12. What Explains *HYNEIO*

This table presents results of quarterly predictive time series regressions of *HYNEIO* over subsequent 4 quarters on selected explanatory variables. *HYNEIO* is the net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012. $HYRET_{q-3:q}$ is Barclay's high-yield excess bond index return over the previous 4 quarters. $LnHYS_{q-3:q}$ is the natural logarithm of high yield share (*HYS)* over the previous 4 quarters. $NBI_{\ q-3:q}$ is defined as total amounts of bond issuance by nonfinancial corporate business during a given quarter out of total bond amounts outstanding in previous quarter, over the previous 4 quarters. $dA/A_{\ q-3:q}$ is a difference in balance sheet assets between end of quarter *q*-4 and end of quarter *q* divided by the assets at the end of quarter *q-4*. *HY Spread q* is the high-yield spread at the end of quarter *q*. $DiffLnRealGDP_{\ q-3:q}$ is a change in log real GDP from end-of-quarter *q-4* to end-of-quarter *q*. $DiffUER_{q-3:q}$ is the difference between the unemployment rate at the end-of-quarter *q* and end-of-quarter *q*-4. $Fed\text{-}DRC_{\ q-3:q}$ in the sum of the federal discount rate changes over the previous 4 quarters. VIX is the end-of-month VXO levels which is based on the VXO is based on the implied volatility of the S&P100 options, available from 1986 and highly correlated with the VIX. $DiffVIX_{\ q-3:q}$ is the difference between end-of-quarter *q* and *q*-4 *VIX* levels. $ExRET_{q-3:q}$ is the cumulative excess return of the market index over the previous 4 quarters. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. *t*-statistics are reported below the coefficient estimates.

	HYNEIO q+1:q+4								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(10)
HYNEIO q-3:q	0.057	0.078	0.039	0.046	-0.016	-0.038	-0.100	0.003	-0.039
	0.40	0.53	0.28	0.30	0.11	0.25	0.62	0.02	0.25
HYRET q-3:q	0.022	-0.002	0.016	0.033	0.016	0.013	0.026	0.009	0.081
	0.63	0.07	0.43	0.85	0.50	0.40	0.66	0.24	0.88
LnHYS q-3:q	-1.630								
	2.44								
NBI q-3:q		-69.346							
		1.88							
dA/A q-3:q			-5.060						
			1.86						
HY Spread q				0.341					
				1.52					
DiffLnRealGDP q-3:q					-51.550				
					1.98				
DiffUER q-3:q						0.921			
						1.96			
Fed-DRC q-3:q							-7.123		
							1.71		
DiffVIX q-3:q								0.185	
								2.82	
ExRet q-3:q									-0.078
									2.51
AdjQSR	0.080	0.041	0.016	0.015	0.059	0.050	0.327	0.148	0.078

Figure 1. ***HYNEIO*** **- 12 month Moving Average**

The figure plots the 12 month moving averages of *HYNEIO* January 1985 to December 2012. *NEIO* is net exchanges (exchanges-in minus exchanges-out) normalized by the end-of-previous month assets. The data is obtained from ICI from February 1984 to December 2012.

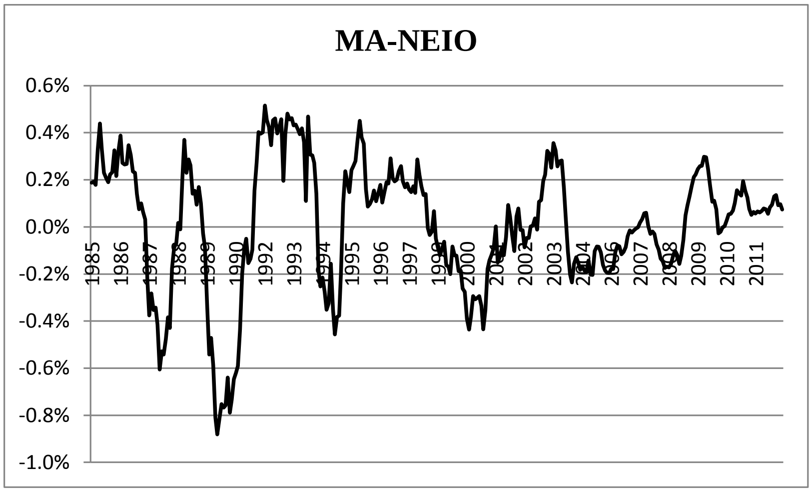


Figure 2. Impulse Response of LnHYS and HYNEIO

This figure plots the orthogonalized impulse response of annual *LnHYS* and *HYNEIO*. We estimate the following annual VAR (vector auto regression) system of *LnHYS* and *HYNEIO* with 1 lag of each of the dependent variables:

$$LnHYS_y = \alpha_1 + \beta_1 LnHYS_{y-1} + \gamma_1 HYNEIO_{y-1} + \varepsilon_{1y}$$
$$HYNEIO_y = \alpha_2 + \beta_2 LnHYS_{y-1} + \gamma_2 HYNEIO_{y-1} + \varepsilon_{2y}$$

The VAR includes 28 annual observations. Graphs a and b plot the cumulative orthogonalized response of *LnHYS* to a one-standard-deviation shock in *HYNEIO* and *HYNEIO* to a one-standard-deviation shock in *LnHYS*, respectively. The graphs start at quarter-0 (marked as 0 on the X-axis) up to year 5 (marked as 5 on the X-axis). The solid black line is the variable response and the dashed gray lines are the 95% confidence intervals. The confidence intervals were estimated numerically using Monte Carlo simulations (see Hamilton 1994, pp. 336–337).

Cumulative Impulse Response of:

(a) *LnHYS* to **a 1 SD Shock in *HYNEIO*** **(b) *HYNEIO*** to **a 1 SD Shock in *LnHYS***

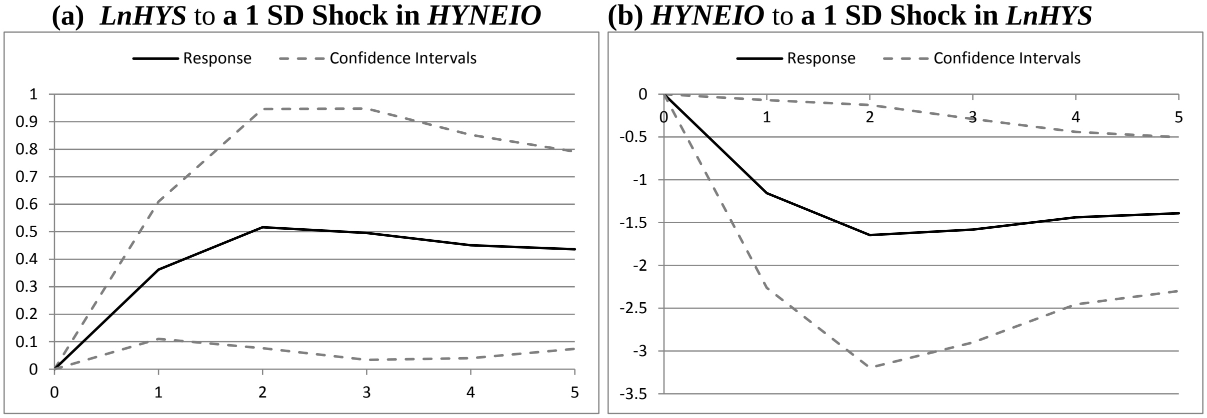


Figure 3. Impulse Response of HY Spread and HYNEIO

This figure plots the orthogonalized impulse response of quarterly HY-Aaa spread and *HYNEIO*. We estimate the following quarterly VAR (vector auto regression) system of *HY-Aaa* and *HYNEIO* with 4 lag of each of the dependent variables:

$$HY-Aaa_q = \alpha_1 + \sum_{t=1}^{4} \beta_{1i} HY-Aaa_{q-i} + \sum_{t=1}^{4} \gamma_{1i} HYNEIO_{q-i} + \varepsilon_{1q}$$
$$HYNEIO_q = \alpha_2 + \sum_{t=1}^{4} \beta_{2i} HY-Aaa_{q-i} + \sum_{t=1}^{4} \gamma_{2i} HYNEIO_{q-i} + \varepsilon_{2q}$$

The VAR includes 115 quarterly observations, and we include lagged *TS* and *TB* as additional control variables. Graphs a and b plot the cumulative orthogonalized response of *HY-Aaa* to a one-standard-deviation shock in *HYNEIO* and *HYNEIO* to a one-standard-deviation shock in *HY-Aaa*, respectively. The graphs start at quarter-0 (marked as 0 on the X-axis) up to quarter 12 (marked as 12 on the X-axis). The solid black line is the variable response and the dashed gray lines are the 95% confidence intervals. The confidence intervals were estimated numerically using Monte Carlo simulations (see Hamilton 1994, pp. 336–337).

Cumulative Impulse Response of:

(a) *HY-AAA* to **a 1 SD Shock in *HYNEIO*** **(b) *HYNEIO*** to **a 1 SD Shock in *HY-AAA***

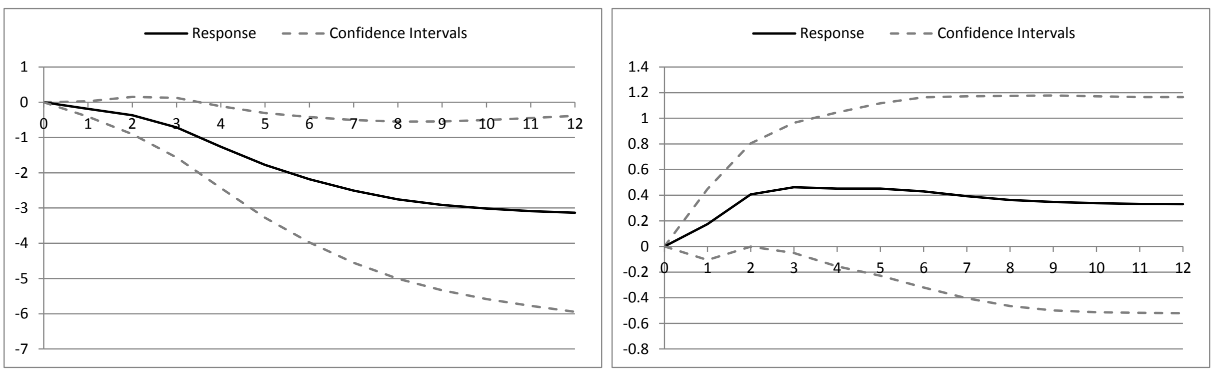


Figure 4. Impulse Response of Excess Bond Premium and *HYNEIO*

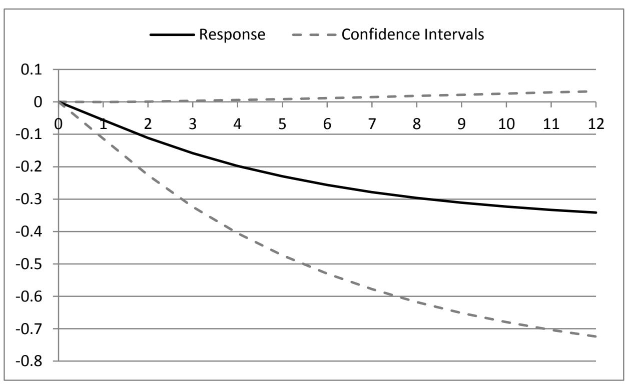
This figure plots the orthogonalized impulse response of quarterly excess bond premium and *HYNEIO*. Excess bond premium (*AveEBP*) is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. We estimate the following quarterly VAR (vector auto regression) system of *AveEBP* and *HYNEIO* with 1 lag of each of the dependent variables:

$$AveEBP_q = \alpha_1 + \beta_1 AveEBP_{q-1} + \gamma_1 HYNEIO_{q-1} + \varepsilon_{1q}$$
$$HYNEIO_q = \alpha_2 + \beta_2 AveEBP_{q-1} + \gamma_2 HYNEIO_{q-1} + \varepsilon_{2q}$$

The VAR includes 106 quarterly observations. Graphs a and b plot the cumulative orthogonalized response of *AveEBP* to a one-standard-deviation shock in *HYNEIO* and *HYNEIO* to a one-standard-deviation shock in *AveEBP*, respectively. The graphs start at quarter-0 (marked as 0 on the X-axis) up to quarter 12 (marked as 12 on the X-axis). The solid black line is the variable response and the dashed gray lines are the 95% confidence intervals. The confidence intervals were estimated numerically using Monte Carlo simulations (see Hamilton 1994, pp. 336–337).

Cumulative Impulse Response of:

(a) *AveEBP* to a 1 SD Shock in *HYNEIO*



(b) *HYNEIO* to a 1 SD Shock in *AveEBP*

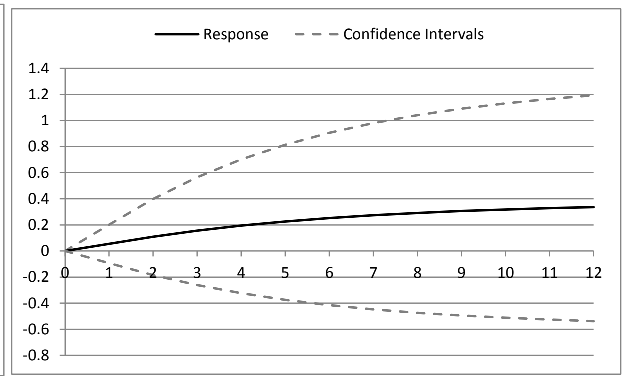


Figure 5. Impulse Response of Real GDP Changes to *HYNEIO* and EBP

This figure plots the orthogonalized impulse response of quarterly changes in GDP (*DiffLnRealGDP*) to a one-standard-deviation shock in *HYNEIO* and *EBP*, where *EBP q* is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. For comparison between HYNEIO and AVeEBP responses, AveEBP one-standard-deviation shock is multiplied by -1. The EBP data ends in September 2010. We estimate the following quarterly VAR (vector auto regression) system of *DiffLnRealGDP*, *HYNEIO*, and excess bond premium with 4 lags of each of the dependent variables:

$$DiffLnRealGDP_q = \alpha_1 + \sum_{t=1}^{4} \beta_{1i} DiffLnRealGDP_{q-i} + \sum_{t=1}^{4} \gamma_{1i} HYNEIO_{q-i} + \sum_{t=1}^{4} \delta_{1i} EBP_{q-i} + \varepsilon_{1q}$$

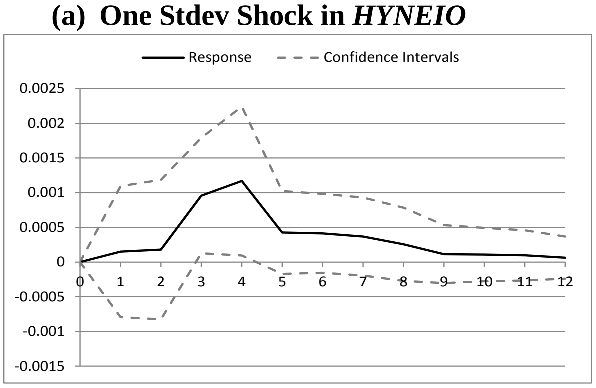
$$HYNEIO_q = \alpha_2 + \sum_{t=1}^{4} \beta_{2i} DiffLnRealGDP_{q-i} + \sum_{t=1}^{4} \gamma_{2i} HYNEIO_{q-i} + \sum_{t=1}^{4} \delta_{2i} EBP_{q-i} + \varepsilon_{2q}$$

$$EBP_q = \alpha_3 + \sum_{t=1}^{4} \beta_{3i} DiffLnRealGDP_{q-i} + \sum_{t=1}^{4} \gamma_{3i} HYNEIO_{q-i} + \sum_{t=1}^{4} \delta_{3i} EBP_{q-i} + \varepsilon_{3q}$$

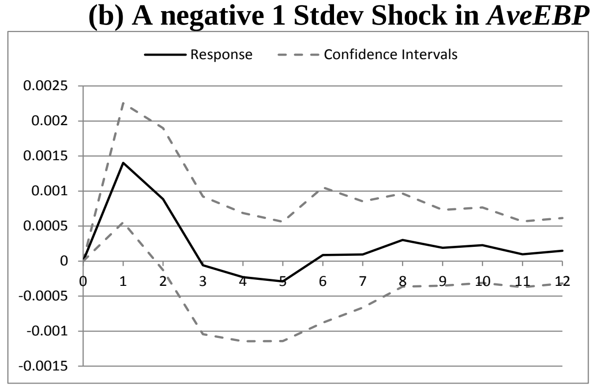
The VAR includes 106 quarterly observations, and we include lagged *TS, DS* and *TB* as additional control variables. Graphs a and b (c and d) plot the non-cumulative (cumulative) orthogonalized response of *DiffLnRealGDP* to a one-standard-deviation shock in *HYNEIO* and *AveEBP*, respectively. The graphs start at quarter-0 (marked as 0 on the X-axis) up to 12 quarters after the shock (marked as 12 on the X-axis). The solid black line is the variable response and the dashed gray lines are the 95% confidence intervals. The confidence intervals were estimated numerically using Monte Carlo simulations (see Hamilton 1994, pp. 336–337).

Non-Cumulative Response of *DiffLnRealGDP* to

(a) One Stdev Shock in *HYNEIO*

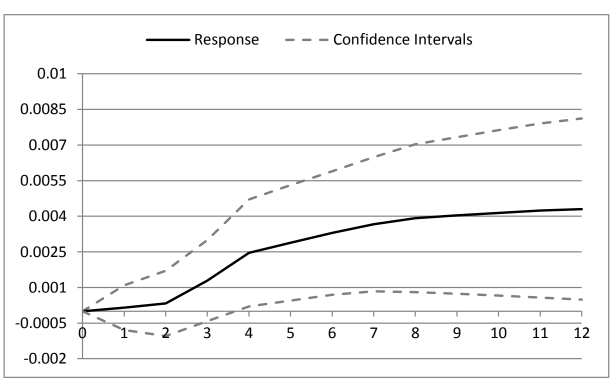


(b) A negative 1 Stdev Shock in *AveEBP*



Cumulative Response of *DiffLnRealGDP* to

(c) One Stdev Shock in *HYNEIO*



(d) A negative 1 Stdev Shock in *AveEBP*

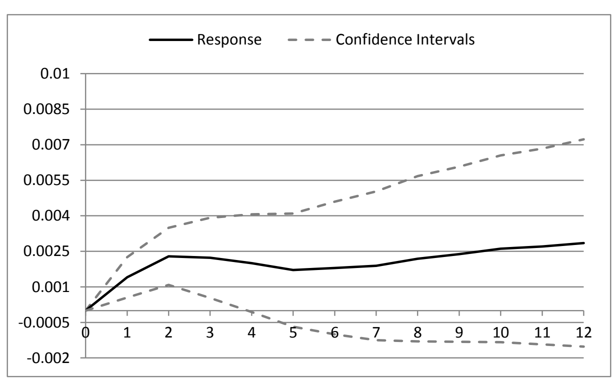


Figure 6. Impulse Response of Unemployment Changes to *HYNEIO* and EBP

This figure plots the orthogonalized impulse response of quarterly changes in unemployment rates (*DiffUER*) to a one-standard-deviation shock in *HYNEIO* and *EBP*, where *EBP q* is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. For comparison between HYNEIO and AVeEBP responses, AveEBP one-standard-deviation shock is multiplied by -1. The EBP data ends in September 2010. We estimate the following quarterly VAR (vector auto regression) system of *DiffUER*, *HYNEIO*, and excess bond premium with 4 lags:

$$DiffUER_q = \alpha_1 + \sum_{t=1}^{4} \beta_{1i} DiffUER_{q-i} + \sum_{t=1}^{4} \gamma_{1i} HYNEIO_{q-i} + \sum_{t=1}^{4} \delta_{1i} EBP_{q-i} + \varepsilon_{1q}$$

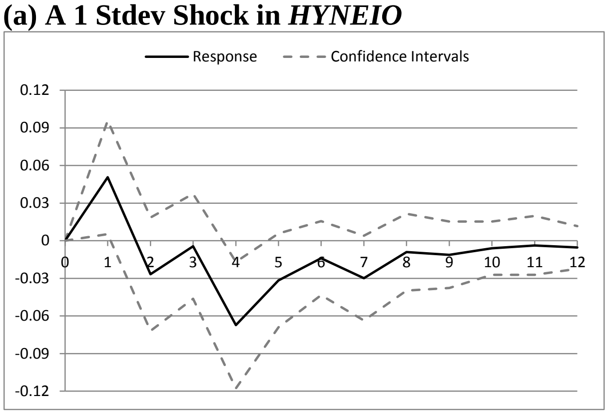
$$HYNEIO_q = \alpha_2 + \sum_{t=1}^{4} \beta_{2i} DiffUER_{q-i} + \sum_{t=1}^{4} \gamma_{2i} HYNEIO_{q-i} + \sum_{t=1}^{4} \delta_{2i} EBP_{q-i} + \varepsilon_{2q}$$

$$EBP_q = \alpha_3 + \sum_{t=1}^{4} \beta_{3i} DiffUER_{q-i} + \sum_{t=1}^{4} \gamma_{3i} HYNEIO_{q-i} + \sum_{t=1}^{4} \delta_{3i} EBP_{q-i} + \varepsilon_{3q}$$

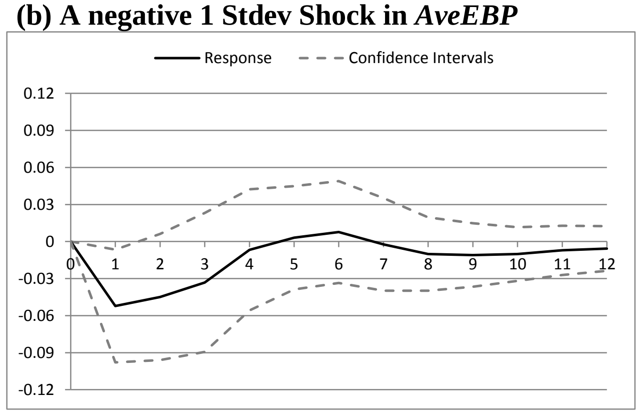
The VAR includes 106 quarterly observations, and we include lagged *TS*, *DS* and *TB* as additional control variables. Graphs a and b (c and d) plot the non-cumulative (cumulative) orthogonalized response of *DiffUER* to a one-standard-deviation shock in *HYNEIO* and *EBP*, respectively. The graphs start at quarter-0 (marked as 0 on the X-axis) up to 12 quarters after the shock (marked as 12 on the X-axis). The solid black line is the variable response and the dashed gray lines are the 95% confidence intervals. The confidence intervals were estimated numerically using Monte Carlo simulations (see Hamilton 1994, pp. 336–337).

Non-Cumulative Response of *DiffUER* to:

(a) A 1 Stdev Shock in *HYNEIO*

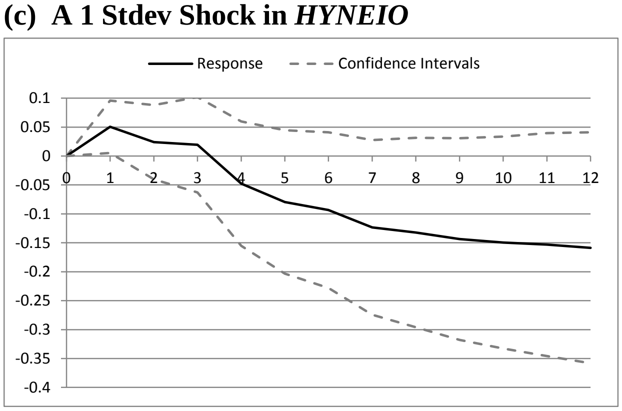


(b) A negative 1 Stdev Shock in *AveEBP*



Cumulative Response of *DiffUER* to:

(c) A 1 Stdev Shock in *HYNEIO*



(d) A negative 1 Stdev Shock in *AveEBP*

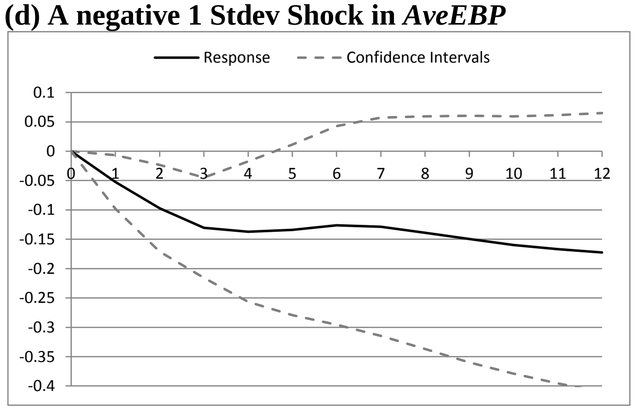
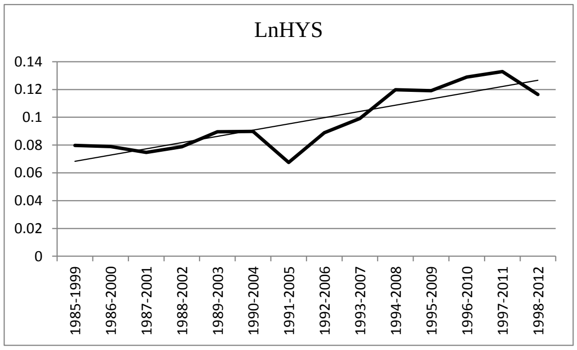


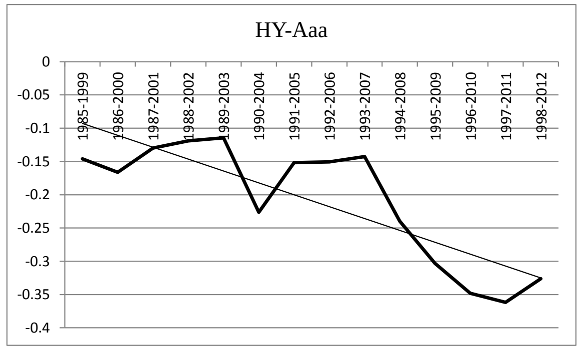
Figure 7. Trends in HYNEIO Regression Coefficients

The figure plots regression coefficients from rolling 15-year windows for *LnHYS*, *HY-Aaa*, *GDP* and *UER*. The plots are based on the regression specification, which includes *HYNEIO*, lag of the dependent variable, *TS*, *DS*, *TB* and *DY*.

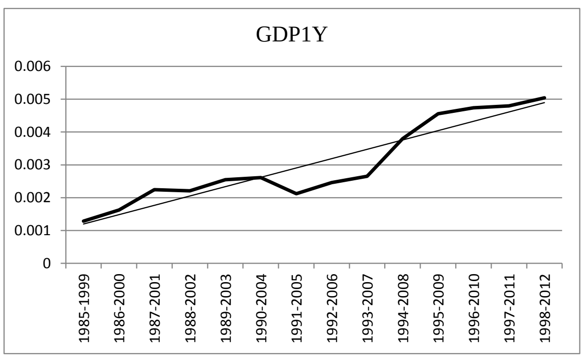
(a) LnHYS



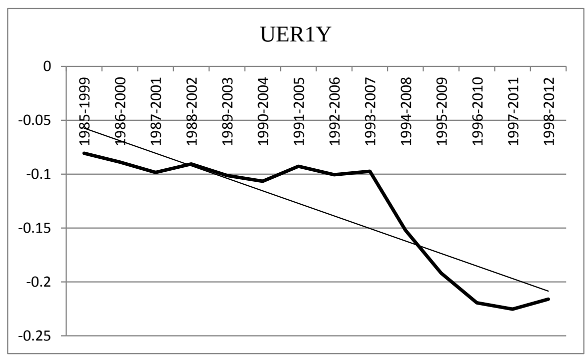
(b) HY-Aaa



(c) LnDiffGDP



(d) UER



Appendix A. ICI's Mutual Fund Categories

This appendix reports statistics for Investment Company Institute (I*CI*) 33 mutual fund investment categories (asset classes). The sample period ranges from January 1984 to December 2012 a total of 348 months. We classify ICI's 33 categories into five major asset classes: "*Equity"*, which includes both domestic and international mutual funds (categories 1-9); "*Corporate Bond"*, which includes both pure and mixed (bond and equity) investments for domestic and international corporate bond mutual funds (categories 10-22); "*Municipal Bonds"*, which includes municipal bonds (categories 23-26), *"Government Bonds"*, which includes government bonds (categories 27-29); and *"Money Market"* which includes money market funds (categories 30-33). In particular, for each of the 33 categories, "*Ave AR*" refers to the time series average of the category's monthly assets to total assets of all categories in ICI data. In a similar manner, "*Med AR*", "*Min AR*" and "*Max AR*", refers to the time series median, minimum and maximum statistics, respectively.

Asset Class	Category	Num Mon	Ave AR	Med AR	Min AR	Max AR
Equity						
Aggressive Growth	1	347	5.71	5.51	2.78	10.24
Growth	2	347	11.88	12.95	5.68	20.46
Growth and Income	3	347	12.86	12.70	7.30	19.26
Income Equity	4	347	1.74	1.65	0.97	2.93
Sector	5	347	1.71	1.93	0.10	3.83
Emerging Markets	6	265	0.69	0.39	0.00	2.12
Global Equity	7	347	2.51	2.69	1.07	4.29
International Equity	8	347	3.42	3.32	0.25	8.02
Regional Equity	9	275	0.57	0.48	0.26	1.23
Corporate Bond						
Asset Allocation	10	275	0.48	0.35	0.16	1.03
Balanced	11	347	2.26	2.44	0.71	3.19
Flexible Portfolio	12	347	1.31	1.59	0.18	2.29
Income Mixed	13	347	1.65	1.74	0.62	2.58
Corporate - General	14	347	0.92	0.90	0.46	1.39
Global Bond - General	15	347	0.47	0.35	0.01	1.44
Strategic Income	16	347	3.36	1.68	0.63	11.15
World Bond	17	275	0.21	0.10	0.02	0.94
Corporate - Short Term	18	275	0.96	0.90	0.64	1.74
Corporate - Intermediate	19	275	0.90	0.83	0.56	1.40
Global Bond - Short Term	20	275	0.24	0.10	0.03	1.45
Mortgage Backed	21	347	1.98	1.25	0.51	5.54
High Yield	22	347	2.06	1.97	1.02	4.14
Muni Bonds						
National Municipal Bond - General	23	347	3.60	2.46	1.59	7.00
State Municipal Bond - General	24	347	2.65	2.15	0.99	5.36
National Municipal Bond - Short Term	25	275	0.54	0.53	0.20	1.09
State Municipal Bond - Short Term	26	275	0.14	0.13	0.03	0.26
Government Bonds						
Government Bond - General	27	347	2.59	0.74	0.34	12.30
Government Bond - Intermediate	28	275	0.57	0.40	0.24	1.33
Government Bond - Short Term	29	275	0.63	0.39	0.20	2.18
Money Market						
National Tax-Exempt Money Market	30	347	3.77	2.80	1.49	8.68
State Tax-Exempt Money Market	31	347	1.23	1.26	0.13	2.34
Taxable Money Market - Government	32	347	7.46	6.87	3.84	16.12
Taxable Money Market - Non-Government	33	347	20.17	17.06	11.13	43.23

Appendix B. Sales, Redemptions, Exchanges-In and Exchanges-Out

Investment Company Institute (*ICI*) provides monthly mutual fund flow information for 33 distinct asset classes (see Appendix A for more details). This Table provides an example of the information provided by ICI, for the high-yield corporate bond category during 1998, where the information is presented in millions of dollars. In particular, the flow information is broken down by ICI into four components: sales and redemptions **-** "Sales" and "Redem"**-** which are actual cash flows that enter or exit the fund family; and exchanges-in and exchanges-out –"Exch In" and "Exch Out" – which are transfers of *existing* cash flows across different asset classes (categories) within the fund family. Net flows, denoted as "*Flow*" is the sum of the four components. "*Net Assets*" is the category's net asset value at the end of the month. Given the growth in the mutual fund industry during our sample period, we normalize the monthly *EIO* and *SR* by the value of total assets at the end of previous month and denote them as *NEIO* and *NSR*, respectively.

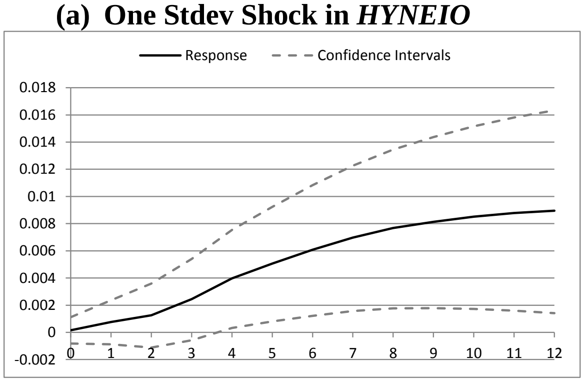
Category # 22	Date	Sales	Redem	SR	Exch In	Exch Out	EIO	Flow	Net Assets
High-Yield	1/31/1998	4,121	1,789	2,332	1,368	667	701	3,033	110,102
High-Yield	2/28/1998	3,742	1,795	1,947	884	681	203	2,151	114,123
High-Yield	3/31/1998	4,281	2,312	1,969	1,251	1,073	178	2,147	117,564
High-Yield	4/30/1998	3,254	2,117	1,138	896	1,197	-301	837	118,986
High-Yield	5/31/1998	3,169	1,810	1,359	923	798	125	1,484	120,342
High-Yield	6/30/1998	3,282	2,093	1,189	884	986	-101	1,088	121,390
High-Yield	7/31/1998	3,365	1,967	1,398	1,398	950	448	1,846	124,234
High-Yield	8/31/1998	2,704	3,824	-1,120	742	3,008	-2,266	-3,386	111,124
High-Yield	9/30/1998	2,657	2,177	480	1,065	1,218	-153	327	110,667
High-Yield	10/31/1998	2,866	2,321	545	1,480	1,646	-166	379	108,296
High-Yield	11/30/1998	5,227	1,892	3,335	2,077	710	1,367	4,702	119,841
High-Yield	12/31/1998	3,206	3,151	55	952	2,011	-1,059	-1,005	117,444
SUM		41,872	27,247	14,626	13,920	14,943	-1,023	13,602	

Appendix C. Impulse Response of Real GDP and UER Changes to 1 SD shock in *HYNEIO and HYNSR*

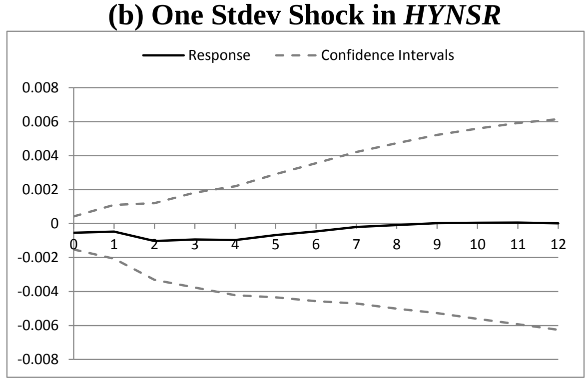
This figure plots the cumulative impulse response of quarterly changes in GDP (*DiffLnRealGDP*) and quarterly changes in unemployment rates (*DiffUER*) to a one-standard-deviation shock in *HYNEIO, HYNSR.* In panel A we augment Table 5's VAR analysis with HYNSR as an additional independent variable. Thus, we estimate a quarterly VAR system of *DiffLnRealGDP*, *HYNEIO*, *HYNSR* and *EBP* with 4 lags of each of the dependent variables. In panel B, we replace *DiffLnRealGDP* with *DiffUER*. The VAR includes 106 quarterly observations. To take into account the fact that HYNEO leads HYNSR (Table 8), EBP (Table 3.B) and *DiffLnRealGDP* and *DiffUER* (Table 5); we set the contemporaneous Cholesky shock order to *HYNEIO*, *HYNSR*, *EBP* and *DiffLnRealGDP (DiffUER)*. Graphs a and b (c and d) plot the cumulative impulse response of *DiffLnRealGDP* (*DiffUER)* to a one-standard-deviation shock in *HYNEIO* and *HYNSR*, respectively. The graphs start at quarter-0 (marked as 0 on the X-axis) up to 12 quarters after the shock (marked as 12 on the X-axis). The blue line is the variable response and the red lines are the 95% confidence intervals. The confidence intervals were estimated numerically using Monte Carlo simulations (see Hamilton 1994, pp. 336–337).

Cumulative Response of *DiffLnRealGDP* to

(a) One Stdev Shock in *HYNEIO*

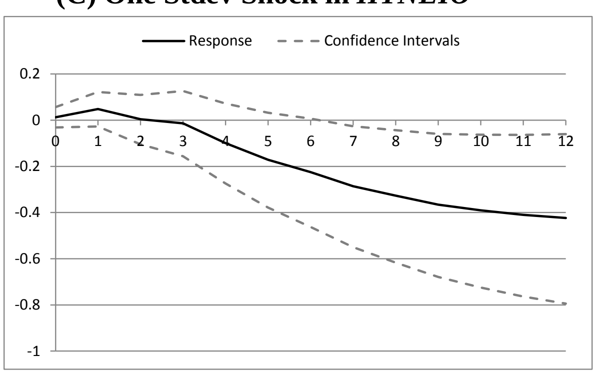


(b) One Stdev Shock in *HYNSR*



Cumulative Response of *DiffUER* to

(C) One Stdev Shock in *HYNEIO*



(d) One Stdev Shock in *HYNSR*