Mutual Fund Flows and Fluctuations in Credit and Business Cycles

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Abstract

Different measures of credit-market overheating are known to precede downturns in real economic activity. There is thus growing interest in understanding credit-market overheating and its origin. We offer an early indicator for all known measures of credit-market overheating. Our measure is based on intra-family flow shifts towards high-yield bond mutual funds. In particular, our indicator positively predicts increases in net bond issuance, growth in financial intermediary balance sheets, shares of high-yield bond issuers, reaching for yield in the credit market, and decreases in different measures of credit spreads. In addition to predicting the credit cycle, our measure directly predicts the business cycle by positively predicting GDP growth and negatively predicting unemployment up to one year earlier than other leading indicators in the literature. We interpret our indicator as an early sign of a shift in investors' demand towards high-risk credit, and so our results support the investors' demand-based narrative of credit cycles. Our indicator can be useful for policymakers trying to take precautionary steps against credit-market overheating.

JEL Classification: E32, G12

Keywords: credit cycle, business cycle, mutual fund flows, high-yield bonds, investor demand, leading indicator

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1. Introduction

A large literature in macroeconomics and finance studies the link between credit markets and macroeconomic cycles. A pattern that emerges from the data is that overheating in credit markets precedes downturns in macroeconomic activity.[1] Such overheating is characterized in different ways, including low credit spreads, high share of low-quality issuers, and high growth in financial intermediaries' balance sheets.

This pattern attracts substantial attention from academics and policymakers, which has been renewed recently in the wake of the great recession. If credit markets are at the root of macroeconomic fluctuations, then it is important to understand better what is driving credit cycles, and perhaps design policy that will moderate them. There is also a constant search for leading indicators that predict credit market overheating. These can be very useful to policymakers so they can prescribe timely measures and to academics so they develop deeper understanding of the underlying causes of credit cycles.

In this paper we show that investors' portfolio choices into high-yield corporate bond mutual funds provide a strong predictor of the overheating in credit markets and the macroeconomic cycle that is associated with it. An increase in our measure in year t predicts the credit-market overheating marked by the other indicators in the literature in years $t+1$ and $t+2$. These other indicators include the share of low quality bond issuers (Greenwood and Hanson, 2013; López-Salido, Stein, and Zakrajšek, 2017), the degree of reaching for yield in the bond market (Becker and Ivashina, 2015), the growth in financial intermediaries' balance sheets (Schularick and Taylor, 2012; Krishnamurthy and Muir, 2015), and various measures of credit spreads (Gertler and Lown, 1999), and in particular the excess bond premium (EBP) recently proposed by Gilchrist and Zakrajšek (2012). In connection with the business cycle, our measure, being a leading indicator to the credit-market overheating, positively predicts GDP growth and negatively predicts unemployment rates in years $t+1$ and $t+2$, before they reverse (together with the other overheating indicators) in year $t+3$.

[1] See, for example, Schularick and Taylor (2012), Jorda, Schularick, and Taylor (2013), and Mian, Sufi, and Verner (2017).

In building the relevant measure of investor choices in mutual funds, we wish to capture changes in investors' demand for high risk credit that show up prior to typical price- or quantity-based market variables. Mutual fund data generally has the potential to provide such information by revealing investors' flows: a measure that is not available in general market contexts. In particular, we focus on *intra-family* flow shifts towards *high-yield* corporate bond funds. To motivate this design, let us explain the two dimensions of this measure, being *intra-family* and *high-yield*.

Two primary reasons lead us to focus on the *intra-family* component. First, intra-family flow shifts are transfers of existing money across asset classes within a fund family and so they precisely reflect investors' decisions of allocating money into one asset class instead of another. In contrast, total net flows, which are typically employed in mutual-fund studies, are driven mainly by investors' long term saving decisions and reflect trends in amounts injected into retirement accounts and asset management more generally. This makes total net flows a much noisier measure of investors' asset allocation decisions. Second, intra-family flow shifts are subject to much lower transaction costs. Many fund families do not charge fees when moving money across funds within the same family (also known as exchanges privileges). In comparison, total net flows are subject to various explicit and implicit costs incurred in sales and redemptions in and out of fund families.[2] Thus, a change in investors' demand for a particular asset will show up more quickly in the intra-family flows.

There are also two reasons for which we focus on shifts into *high-yield* bond funds. First, the vast literature on credit markets and business cycles has shown the importance of the high-yield segment of the credit market in detecting economic changes. For example, Gertler and Lown (1999) show that high-yield bond spreads provide a leading indicator for economic cycles, which they attribute to the fact that firms in this segment of the market are highly sensitive to financial frictions. More recently, Greenwood and Hanson (2013) and also Lopez-Salido, Stein, and Zakrajšek (2017) show that financing activities of below-investment-grade firms have strong predictive power for future economic fluctuations, which they attribute to investors' sentiment. Second, unlike investors in equity mutual funds, who are very heterogeneous, investors in high-

[2] Indeed, intra-family flow shifts are often marketed as an asset allocation tool for these reasons.

yield bond funds tend to be more homogeneous and are mostly wealthier and savvier than average. Hence, their portfolio choices may provide a useful barometer of economic states. [3]

We obtain the data on intra-family flow shifts from the Investment Company Institute (ICI). 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. Our measure is the net exchanges (exchanges in minus exchanges out) for high-yield corporate bond funds (hereafter, HY-NEIO).[4] We view HY-NEIO as a measure that isolates changes in asset allocation decisions between high-yield credit and other asset classes. For comparison, we also define HY-NSR, the net of sales and redemptions components in high-yield bond funds. HY-NSR accounts for a much larger portion of total net flows compared with HY-NEIO. We verify that HY-NEIO captures early shifts in investor demand. In particular, we show that HY-NEIO positively predicts, up to 12 months in advance, HY-NSR. HY-NEIO also predicts mutual fund flow components into the other asset classes, such as stocks, investment-grade and government bonds, and money market funds. This confirms our conjecture that HY-NEIO is a good barometer to detect changes early.

Let us now describe our results in more detail. In a recent influential paper, Greenwood and Hanson (2013) show that the share of high-yield bond issuance, or high-yield share (HYS), is an indicator of credit-market overheating that predicts an increase in credit spread. More recently, Lopez-Salido, Stein, and Zakrajšek (2017) show that HYS can predict an upcoming macroeconomic downturn. Our first finding is that our indicator from mutual-fund flows HY-NEIO is an early indicator by positively predicting the HYS over the next year. In contrast, an increase in the HYS does not positively predict an increase in HY-NEIO. Similarly, we find that HY-NEIO positively predicts the degree of reaching for yield, which we define as the bond

[3] One distinguishing feature of high-yield bond mutual funds is that they are not usually offered in corporate defined contribution plans. According to a 2016 report on Vanguard defined contribution plan data "How America Saves", only 18% of pension plans offer high-yield mutual funds, and only around 5% of the pensioners choose to invest in them. Another important point is that high net worth individuals choose to invest in high-yield mutual funds instead of trading these bonds directly because of the significant cost of trading high-yield bonds. High-yield mutual funds offer a liquid vehicle for investing in these illiquid assets.
[4] To be more precise, HY-NEIO stands for high-yield normalized exchanges in and out, where net exchanges are normalized by high-yield corporate bond fund assets.

amount-weighted average of corporate bond yields divided by the simple average of the yields in each rating.[5]

In the next set of predictive regressions, we explore the ability of HY-NEIO to predict business cycle predictors that are based on credit spreads. In particular, we examine the Baa-Aaa spread (the default spread), the high-yield spread of Gertler and Lown (1999), and the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012). We find that HY-NEIO negatively predicts these predictors up to one year in advance, indicating that when investors shift their portfolio compositions toward high-yield bonds, future bond prices are elevated and credit spreads become narrower. These results are particularly important, given the increasing importance of credit spreads as an indicator for the economic recessions driven by credit crunch such as the 2008 financial crisis, as shown in Krishnamurthy and Muir (2015) and Lopez-Salido, Stein, and Zakrajšek (2017).

While the above measures deal with the price of credit, another important set of variables highlighted in the literature in connection with credit-market overheating revolves around quantities of credit. Linking our measure to these variables, we show that HY-NEIO predicts growth in the balance sheets of financial intermediaries and total net amounts of corporate bonds issued in the economy. Schularick and Taylor (2012) and Krishnamurthy and Muir (2015) argue that growth in leverage in the financial sector combined with negative shocks causes financial crises. Hence, predicting the financial sector growth is a critical issue, pointing to the importance of the information contained in HY-NEIO. Our results are quantitatively large; for example, a one-standard-deviation increase in HY-NEIO translates into a 0.75%-1.00% growth in intermediary balance sheets. Importantly, the results are robust after controlling for other indicators mentioned above, such as HYS and EBP.

After demonstrating the predictability of these forecasting variables found in the previous studies, an important question is whether HY-NEIO can directly serve as a useful early indicator for business cycle fluctuations. Thus, we examine the forecasting power of HY-NEIO for future GDP growth and unemployment rate changes in comparison with the forecasting power of credit

[5] This measure captures relative fraction of higher-yielding corporate bonds in a given rating. See Choi and Kronlund (2017) for more details.

spreads and the EBP. 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 the existing predictors. We find that this is indeed the case. First, in vector autoregressions (VAR), the impulse response analysis shows that a shock to HY-NEIO predicts a positive spike in GDP growth and a negative spike in unemployment rate changes up to eight quarters in advance. In contrast, the existing leading predictors of business cycles, e.g., the EBP of Gilchrist and Zakrajšek (2012), predict future GDP growth and changes in unemployment rates in a shorter horizon over a period of two to four quarters. 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, HY-NEIO exhibits a strong forecasting power for future GDP growth and changes in unemployment rates. More importantly, HY-NEIO 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 forecasting power.

The results so far suggest that HY-NEIO contains valuable information for policymakers and that it should be part of the Federal Reserve's toolkit. To demonstrate this more directly, we ask whether HY-NEIO can predict future monetary policy changes. Indeed, we find that HY-NEIO positively predicts tightening of future monetary policy, as measured by 2-year changes in the Fed's discount rate, actual fed fund rate, and Romer and Romer's (2004) monetary policy shocks measure. HY-NEIO predicts these policy changes up to 12 months in advance compared with the previous indicators EBP and HYS. In contrast, monetary policy changes do not predict future HY-NEIO. Furthermore, HY-NEIO is practically helpful in real-time forecasting. In out-of-sample tests, we show that employing HY-NEIO produces the lowest average and dispersion in root-mean-squared forecasting errors, compared with other leading indicators.

Our interpretation of the results is that HY-NEIO provides an early indication of changes in appetite for risk by debt investors. As we mentioned above, this measure is capable of detecting these changes early because it contains information about the first changes in asset allocation by a group of relatively savvy investors. Papers by Greenwood and Hanson (2013) and Lopez-Salido, Stein, and Zakrajšek (2017) attribute the overheating in credit markets to investors' sentiment, but do not provide a clear proxy for changes in investor demand. Our HY-NEIO measure gets much closer to detecting changes in investor demand. In that, we provide support for their assertion that changes in investors' sentiment or appetite for risk are important drivers of the credit cycle. The facts that our measure detects the signs of overheating so much ahead of the other indicators and even predicts them make it very useful as a leading indicator for policymakers.

The demand shock we capture with the HY-NEIO measure is very different from the sentiment described in the model of Bordalo, Gennaioli, and Shleifer (2016) as a driver of credit overheating. They build on a notion of extrapolative beliefs, where investors condition on recent good outcomes to believe that future outcomes will also be good, and show how this can cause amplification in credit cycles.[6] However, the behavior of investors that is captured by HY-NEIO anticipates the cycle rather than follows it. More flow shifts to high-yield funds predict brighter credit and economic conditions, rather than follow such conditions. This is in direct contrast to the behavior of indicators like HYS. It is of course possible that beliefs of the kind in Bordalo, Gennaioli, and Shleifer (2016) or financial frictions as in Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) magnify the overheating, but the demand shock reflected in mutual funds portfolio shifts seems to be what gets the cycle started.

The investors shifting their money into high-yield funds exhibit a "smart-money" behavior in that a trading strategy based on the signal from HY-NEIO is highly profitable with an annual Sharpe Ratio of 1.00. This profitability comes from the fact that intra-family shifts into high yield funds, as captured by HY-NEIO, are fast-moving money that is informative of future aggregate investor demand captured by slow-moving total net flows. Indeed, HY-NEIO forecasts future HY-NSR and net flows to equity funds up to 12 months in advance, while all these other flow components do not possess any predicting power for future HY-NEIO. Again, our interpretation is that HY-NEIO is an early indicator of demand changes, and this is why it is profitable. Without knowing more about the identity of investors in high-yield funds, it is harder to tell a story where they simply forecast everything that is about to come better than any other investors in the economy. Note also that HY-NEIO is a small component and so it is implausible to think that it is affecting the cycle. Rather, it is likely to be a very informative reflection of the demand shock that ignites it.

[6] See also Greenwood, Hanson, and Jin (2016).

Other than the papers about the credit cycle and its connection to the business cycle that we mentioned so far, our paper is related to the vast literature that studies the ability of market prices to predict future economic activities. Papers in this literature include Fama (1981), Harvey (1988), Estrella and Hardouvelis (1991), Gertler and Lown (1999), Ang, Piazzesi, and Wei (2006), Gilchrist, Yankov, and Zakrajšek (2009), and Gilchrist and Zakrajšek (2012). See also Stock and Watson (2003) for a summary of the literature. Instead, our predictive variable is based on mutual fund flows.

There is also literature that uses fund flows to try to forecast economic outcomes, e.g., Warther (1995), but usually with limited success. In most cases, papers employing mutual-fund data rely on total flows. An exception is Ben-Rephael, Kandel, and Wohl (2012) that study the behavior of intra-family exchanges in and out of equity funds, using the ICI data like us. However, the behavior of these intra-family flows for equity funds, as they find, is very different than what we find here for high-yield funds. In particular, for equity, these flows follow the cycle rather than predict it, i.e., investors exchange into equity funds when equity prices are high, and so the behavior looks more like "dumb money". This is consistent with our premise that investors in equity funds are a very diverse group and the majority of them might exhibit very different behavior from the relatively savvy investors in the high-yield funds.

Finally, our paper is related to the recent literature that studies the behavior of investors and managers in corporate bond funds, including the papers by Feroli, Kashyap, Schoenholtz, and Shin (2014), Chen and Qin (2016), Goldstein, Jiang, and Ng (2017), and Choi and Kronlund (2017). Corporate bond funds have grown tremendously in recent years and these different studies are trying to assess their behavior, how different they are from equity funds, and what implications they might have for market stability. Our focus is very different, as we are exploring the predictive ability of a certain component of flows into corporate bond funds for general market outcomes.

The remainder of this paper is organized as follows: In Section 2, we describe the data and the construction of our main variable. Section 3 describes results on the predictive power of intra-family flow shifts for key indicators of credit cycles. In Section 4, we use the intra-family flow shifts to predict the business cycle and monetary policy. Section 5 explores the "smart-money" behavior of intra-family shifts into high yield funds. In Section 6, we provide extensions and robustness tests. Section 7 concludes.

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 (bond-only) and balanced (equity and bonds) funds investing in domestic and international markets.[7]

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

Appendix B provides an example of the HY 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. Even though investors shifted their capital away from the HY category possibly due to the increased risk in the market, total annual net flows into HY bonds were positive (13.6 billion dollars), driven by large SR (14.6 billion dollars). This example shows that EIO should

[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. Excluding these funds does no materially change our results.

provide a better sense of investors' view of economic conditions, while total net flows or SR can be misleading.

2.2. Main Variable Construction

We construct monthly HY-NEIO, 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, following the approach similar to Ben-Rephael, Kandel and Wohl (2012). This normalization allows us to account for natural growth in the mutual fund industry during our sample periods. In a similar manner, we construct monthly HY-NSR as the normalized sales minus redemptions (NSR) of the HY category, 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., IG-NEIO and IG-NSR for the IG category, EQ-NEIO and EQ-NSR for the EQ category, and GM-NEIO and GM-NSR for the GM category.

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 HY-NSR is 0.696%, showing increasing capital inflows into HY bond funds during the sample period, while the average of HY-NEIO 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 NEIO and NSR within and across asset classes. Panel B1 indicates that NEIO and NSR share a positive component, where the correlations range from 0.02 (GM) to 0.51 (HY). Panel B2 reports correlations of NEIO across asset classes. The panel shows that HY-NEIO, IG-NEIO, and EQ-NEIO are all strongly and negatively correlated with GM-NEIO, suggesting that investors shift money in and out of the GM category when investing in higher risk asset classes. In contrast, Panel B3 shows that correlations between NSR components are positive, showing that net flows into funds across different asset classes tend to commove together. Overall, the correlations reported in Panel B also suggest that NEIO is a cleaner signal for investor portfolio allocation choices than NSR.

Figure 1 plots the 12-month moving averages of HY-NEIO. The peaks and troughs of HY-NEIO overlap with some the known market events. For example, there are large troughs before the three NBER recessions. Importantly, HY-NEIO also decreases significantly before major crisis and credit events, e.g., the 1987 market crash, the Mexican Peso crisis in 1994, and the European sovereign debt crisis in early 2010.

3. Intra-Family Flow Shifts and Credit Cycle Fluctuations

In this section, we examine whether HY-NEIO can predict leading indicators for credit and business cycles suggested in the prior literature. In particular, we focus on the following indicators: (1) the high-yield share (HYS) of Greenwood and Hanson (2013), which measures the quality of corporate bond issuers and also credit-market sentiment according to Lopez-Salido, Stein, and Zakrajšek (2017); (2) a measure of reaching for yield (RFY), which captures the degrees of risk-taking in the corporate bond market; and (3) aggregate credit spreads and also the EBP of Gilchrist and Zakrajšek (2012), the latter of which has shown to have a strong predicting power for future economic activities. In addition, we also examine the predictability of total net bond issuance and balance sheet growth in financial intermediaries, the latter of which Krishnamurthy and Muir (2015) argue is an important indicator for the severity of financial crisis.

In our analyses throughout the paper, we control for variables that are previously found to be important in predicting credit and business cycle variation. In particular, we control for the term spread (TS), the difference between 10- and 1-year Treasury yields; the default spread (DS), the difference between Baa- and Aaa-rated corporate bond yields; the 3-month T-bill rate (TB); the dividend yield (DY), the sum of dividends for past 12 months divided by total market capitalization; and lagged returns on corporate bond indices. In addition, throughout our tests, we contrast the predictive ability of HY-NEIO with that of HYS and EBP, since both are important predictors of the credit cycle and business cycle in the recent literature.

3.1 Predicting the High-Yield Share

According to Greenwood and Hanson (2013), the HYS of corporate bond issuers is a strong predictor for returns on corporate bonds. When credit markets are booming and thus the 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 Zakrajšek (2017) use the HYS as a proxy for credit market sentiment, which they show can predict future economic fluctuations. We examine whether HY-NEIO can predict the HYS of corporate bond issuers.

The 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 the Mergent Fixed Income Database (FISD), using Moody's credit ratings. As in Lopez-Salido, Stein, and Zakrajšek (2017), we use the log of HYS in regression analyses.

Table 2 presents the regression results.[8] In Columns 1 through 3, we regress the average of log HYS over four quarters on average HY-NEIO over the past four quarters. We find that HY-NEIO positively predicts the future HYS. The results are quite robust to adding various control variables. The economic magnitude of the coefficient estimates on HY-NEIO is also substantial. For example, a one-standard-deviation increase in HY-NEIO is associated with a 3.8% increase in log HYS, which implies that 3.8% of more junk-rated issuers in the economy.

We also examine the dynamic relation between HY-NEIO and the HYS using an annual VAR (vector autoregression) with one lag of each variable. Figure 2 plots the impulse response functions. In particular, the response of the HYS to a one-standard-deviation shock in HY-NEIO is positive and significant, consistent with our predictive regressions in Table 2. This is consistent with HY-NEIO 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 HY-NEIO to a one-standard-deviation shock in log HYS, is negative and significant, suggesting that HY-NEIO is trending down after an increase in HYS.

[8] In Table 3 we estimate the relation between HY-NEIO and HYS and RFY levels. Using first differences of HYS and RFY yields qualitatively similar results.

3.2 Predicting Reaching for Yield

We further examine whether HY-NEIO 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 the corporate bond market. As Rajan (2013) and Stein (2013) note, an ultra-low interest rate environment can lead to excessive risk-taking and credit-market overheating 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 (Becker and Ivashina, 2015). 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 (Choi and Kronlund, 2017), particularly when the credit market is booming.

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

$$RFY_{jt} = \frac{\Sigma\, w_{jt} y_{jt}}{\Sigma \frac{1}{n} y_{jt}}$$

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

Table 2 Columns 4 through 6 present the regression results of RFY on lagged HY-NEIO. We find that HY-NEIO strongly predicts future RFY. A one-standard-deviation increase in HY-NEIO is associated with 5% to 5.5% increases in RFY. Moreover, controlling for other variables does not change HY-NEIO's predictive ability. Interestingly, the lagged HYS is marginally significant in predicting future RFY, which suggests that the HYS is a useful indicator for credit market overheating, consistent with evidence in Lopez-Salido, Stein, and Zakrajšek (2017). Note also that the EBP does not help predicting future RFY, as shown by insignificant, positive coefficients.

In summary, the results provided in Table 2 show that HY-NEIO consistently predicts indicators which associated with the credit cycles. That is, investor flow shifts into HY bond funds signals that future credit market conditions will improve.

3.3 Predicting Credit Spreads and the Excess Bond Premium

Recent studies have found that credit spreads are important indicators for business cycle variation. For example, Gilchrist and Zakrajšek (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. Krishnamurthy 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 business cycles.

Given that HY-NEIO is an early predictor for the HYS and RFY, an important and interesting question that arises is whether HY-NEIO can predict credit spreads as well. We focus on the high-yield spread (HY-Aaa spread) and the default spread (Baa-Aaa spread) as well as the 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 the future high-yield and default spreads on HY-NEIO. In particular, we regress one-year future spreads on lagged HY-NEIO, lagged dependent variables, and other control variables. Our results show that HY-NEIO negatively predicts both the high-yield and default spreads over the next year, across all the specifications considered. In Columns 1 through 4, for example, a one-standard-deviation decrease in HY-NEIO translates into 0.56%-0.79% increases in the high-yield spread. In addition, the coefficients on lagged HY-NEIO are negative and statistically significant at the conventional levels, as shown in columns (5) through (8). Summarizing the results, a higher allocation of investor money into high yield funds predicts lower credit spreads (i.e., higher corporate bond prices) in the next year.

Figure 3 depicts the impulse response functions from a quarterly VAR estimation of HY-NEIO and the high-yield spread. The results are consistent with the regression results in Panel A of Table 3. A negative one-standard-deviation-shock in HY-NEIO is associated with an increase in the high-yield spread, which lasts around 8 quarters. The signs of reversal from quarter 9 indicate that market conditions revert to mean at some point.

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

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

3.4 Predicting Growth in Financial Intermediary Balance Sheets and Aggregate Bond Issuance

A growing body of literature shows the importance of the role played by changes in the balance sheets of financial intermediaries in 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 the crises. In this section, we examine whether HY-NEIO positively predicts growths in financial intermediary balance sheets measured as quarterly differences in the financial sector's assets divided by the previous quarter's assets.[9] In addition,

[9] The data are obtained from Table L.129 of the Federal Reserve Flow of Funds (see also Adrian, Etula and Muir, 2014).

we examine whether HY-NEIO can predict growth in credit, as measured by the total net amounts of corporate bond issuance (NBI) by nonfinancial corporate business.[10]

Table 4 reports the predictive regression results. In Columns 1 through 3, we regress quarterly growths in intermediary balance sheet assets on HY-NEIO and other explanatory variables. The results indicate that HY-NEIO positively predict balance sheet growths in the next quarter. For example, the coefficient estimates on HY-NEIO are all positive and statistically significant at the 5% level. A one-standard-deviation increase in HY-NEIO translates into a 0.91% to 1.08% growth in intermediary balance sheets for the next quarter. The results are robust to controlling for past cumulative returns on corporate bonds, 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 HY-NEIO. We find that the coefficient estimate on HY-NEIO is positive and also statistically significant at the 5% level. The economic significance is also sizable. A one-standard-deviation increase in HY-NEIO is associated with an increase in NBI by around 0.30% in the next quarter. 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) , which can simultaneously drive both NBI and HY-NEIO. Overall, the results in Table 4 suggest that HY-NEIO 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 the 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.

[10] Specifically, we calculate NBI as the ratio of new bond issue amounts to total bond amounts outstanding in nonfinancial corporate businesses, available from the flow of funds data from the Federal Reserve.

4. Intra-Family Flow Shifts and Economic Cycle Fluctuations

Consistent with our idea that intra-family flow shifts are the most highly sensitive component of mutual fund flows that capture investor belief for future credit conditions, our results so far show that HY-NEIO predicts leading business cycle indicators suggested in the literature. We ask an important follow-up question that arises from our findings: can HY-NEIO predict economic fluctuations *earlier* than leading indicators in the literature, e.g., credit spreads, the EBP, and the HYS? In this section, we provide strong empirical evidence showing that HY-NEIO is an early indicator for future GDP and unemployment rate changes as well as monetary policy changes. In addition, we provide out-of-sample test results of the predictability of these variables.

4.1 Predicting Real GDP and Unemployment Rates

In Table 5 Panel A, we present results from multiple regressions of real GDP growth on HY-NEIO and other control variables including the HYS and EBP. In Columns 1 through 1, we find that HY-NEIO can positively predict real GDP growth for the next four quarters. The results are robust across all the four specifications with the t-statistics ranging from 2.54 to 3.45. In comparison, the coefficient estimates on the EBP are only marginally statistically significant at the 10% level and those on the HYS are not statistically significant at conventional levels, showing that intra-family flow shifts provide a strong signal for future economic fluctuations even after controlling for existing leading indicators.

To examine longer-run predictability of economic activities, in columns (5) through (8) we regress real GDP growth over the next eight quarters on HY-NEIO. The results show that the regression coefficients on HY-NEIO are positive and statistically significant at the 5% level, thus indicating that HY-NEIO predicts GDP growth over the longer horizons. In contrast, we do not find the coefficient estimates on either the EBP or HYS are statistically significant, showing that the predicting power of these variables is concentrated largely in the shorter horizons (i.e., shorter than the first four quarters). Note that the coefficients on HY-NEIO in Columns 5 through 8 tend to be higher than those in Columns 1 through 4, indicating that HY-NEIO can predict both the first four quarter and the next four quarter GDP growth.

The results provided in Panel A suggest that HY-NEIO is an early business cycle indicator by predicting real GDP growth up to eight quarters in advance. Alternatively, one can also interpret these results to imply that HY-NEIO predicts more persistent and longer-lasting component in real GDP growth, while the EBP predicts a more transient component. To distinguish these two possibilities, we plot the impulse responses of real GDP growth to one-standard-deviation shocks in HY-NEIO and EBP, shown in Figures 5(a) and 5(b), respectively, using the VAR. A comparison of the two figures shows that HY-NEIO is an early indicator, compared to the EBP. A one-standard-deviation shock in HY-NEIO leads to a statistically significant change in GDP growth only after five quarters, as can be seen from the confidence intervals of the impulse response. In contrast, Figure 5(b) indicates that a one-standard-deviation shock in the EBP affects GDP immediately starting one quarter after the shock. Moreover, the effect of the EBP seems to decay fairly quickly while the effect of HY-NEIO lasts for 8 quarters. In Appendix C, we also verify that differences in the impulse responses to HY-NEIO and EBP shocks are statistically significant at the 1% level, using Monte-Carlo simulations to calculate their confidence intervals. In particular, Panel A in Appendix C shows that the difference in HY-NEIO and EBP impulse response functions for quarters 1 and 2 is -0.0023 with a *p*-value of 0.03, thus showing that the response of GDP to the EBP is more immediate. In contrast, the difference in impulse responses for quarters 3 to 9 is 0.005 with a p-value of 0.01, confirming that HY-NEIO is an early indicator for real GDP growth.

In Panel B of Table 5, we examine the predictability of unemployment rate changes using HY-NEIO, similar to our analyses in Panel A. Our conclusions from these results are largely the same as those from the results based on GDP growth. In particular, the coefficient estimates on HY-NEIO are highly statistically significant in the next four quarters (Columns 1 through 4) and also in the next eight quarters (Columns 5 through 8), while the coefficient on the EBP is significant at the 5% level only during quarters 1 through 4 and the coefficients on the HYS are not statistically significant.

Similar to the impulse response results plotted in Figure 5 for GDP growth, Figure 6 shows that HY-NEIO is an early predictor for future unemployment rate changes, compared with the EBP. As in Figure 5, the impulse responses indicate that a shock in HY-NEIO leads to a negative peak only after 8 quarters, while a shock in the EBP appears immediately and reverts after a few quarters.

The Wald test results provided in Panel B of Appendix C also confirm that the EPB moves first in quarters 1-2 (a p-value of 0.04) while the response to HY-NEIO kicks in in Quarters 3-11 (a p-value of 0.02). Overall, these results confirm that HY-NEIO is an early indicator for future economic activities, i.e., real GDP growth and unemployment rate changes.

Figure 7 depicts the timeline of HY-NEIO, the HYS, and credit spreads in the order of their predicting power for GDP growth and unemployment rates. HY-NEIO in year *t* leads the other indicators by positively predicting the HYS and negatively predicting credit spreads in year *t+1*. It also predicts GDP and unemployment rates in a longer horizon up to year *t+2*. In comparison, as Lopez-Salido, Stein, and Zakrajšek (2017) show, an increase in HYS accompanied by a decrease in credit spreads in year *t+1* is associated with a decline in economic activity in year t+3 (i.e., a decrease in GDP in year *t+3*) and also an increase in credit spreads in year *t+3*. Greenwood and Hanson (2013) also provide similar findings, in which an increase in the HYS in year *t+1* is followed by an increase in credit spreads in year *t+3* (or a decrease in corporate bond returns in year *t+3*). In sum, HY-NEIO moves a year in advance before an onset of a sentiment-driven credit cycle suggested in Lopez-Salido, Stein, and Zakrajšek (2017).

4.2 Predicting Future Monetary Policy

Table 6 examines the predictability of monetary policies. We use three measures of monetary policy changes: the Federal Reserve's discount rate (lending rate at the discount window), the federal funds rate, and Romer and Romer's (2004) measure (RR) of monetary shocks, the latter of which captures unexpected shocks in Fed policies.[11] Given the persistent nature of changes in monetary policy, we focus on two-year horizon policy changes, where we regress future 24 months changes in the discount rate, the federal funds rate, and the R&R measure on HY-NEIO.

Table 6 presents the regression results. Columns 1 and 2 indicate that HY-NEIO positively predicts future discount rate changes, even after controlling for lagged monetary policy changes and other control variables. The predicting power of HY-NEIO is also economically significant. A one-standard-deviation shock is associated with up to a 0.60% change in future discount rates (Column 2). We also find that the coefficients on the HYS in Columns (1) and (2) are positive and

[11] The updated data for the Romer and Romer (2004) measure are available up to December 2007 at http://www.basilhalperin.com/blog/2013/12/updated-romer-and-romer-2004-measure-of-monetary-policy-shocks/.

statistically significant. We find similar results in columns 5-6 and 9-10 based on the federal funds rate and RR, respectively, showing that an increase in HY-NEIO or the HYS forecasts tighter monetary policies for the next 8 quarters. Note that these results do not necessarily imply that investors (as proxied by intra-family flow shifts) can predict future monetary policies. Rather, it is possible that monetary policies respond to booming credit conditions.

To further examine the timing of predictability, we regress future 24-months changes in monetary policy on explanatory variables by skipping the first 12 months, shown in Columns 3-4, 7-8, and 11-12. That is, we regress discount rate changes from 13 to 36 months ahead on current variables. The results shown in Columns 3 and 4 indicate that HY-NEIO coefficient remains positive and significant, while the HYS loses its predicting ability, thus showing that HY-NEIO is an early predictor for monetary policies. We find similar results in Columns 7-8 and 11-12 for the federal funds rate and RR, respectively. Note also that throughout all specifications in 1 to 12, HY-NEIO is the only predictor that remains statistically significant. Combined, Table 6 show that HY-NEIO is a strong early indicator for future monetary policies as well.

4.3 Would Using HY-NEIO Have Helped Predict Economic Cycles?

Our results presented thus far show that HY-NEIO has superior in-sample explanatory power for future economic cycles. A natural question to follow is whether it would have been practically helpful to employ HY-NEIO in real-time forecasting. We answer this question by performing pseudo-out-of-sample analyses that examines forecasting errors of GDP growth and unemployment rate changes.

Table 7 reports the root-mean-squared forecasting errors (RMSE) of one- or two-years changes in real GDP growth (*GDP*) and changes in unemployment rates (*UR*), using regression coefficients obtained from 10-year rolling estimation windows. We examine the forecasting errors of both univariate and multiple regression models and compare RMSEs from using HY-NEIO with using other economic indicators including HYS and EBP as well as the control variables in our predictive regressions. To prevent look-ahead bias in forecasting, we use information that is available only at the time of forecast when estimating regression coefficients. Specifically, in each quarter *q*, we first estimate regression coefficients of our forecasting models using past 10-years of observations of explanatory and dependent variables. Then, using the coefficient estimates together with the explanatory variables observed in quarter *q*, we forecast the dependent variables over the next four quarters (*q+1:q+4*) and eight quarters (*q+1:q+8*).

Panel A of Table 7 reports RMSEs from using univariate regression models in which we compare the forecasting performance of eight different variables. The first is the lagged dependent variable, *DEP q-3:q*. The next four variables are the control variables in the predictive regressions, namely, *DS*, *TS*, *TB*, and *DY*. The last three are HY-NEIO, the HYS, and the EBP. In addition to RMSEs, we also report the ratios of RMSEs with respect to the RMSE from the benchmark model, which employs only *DEP* as a sole predictor, and the relative rankings of RMSEs among the eight predictors.

In Panel A, we find that HY-NEIO outperforms all the other predictors in forecasting one- and two-year GDP growth and two-year unemployment rate changes. For example, using HY-NEIO produces 10.7% (=$1 - 3.49\%/3.91\%$) and 10.0% (=$1 - 3.49\% \,/\, 3.88\%$) lower RMSEs relative to using the HYS and EBP, respectively, in forecasting two-year horizon GDP growth. Only exception is the forecasting of one-year unemployment rate changes, in which HY-NEIO is ranked the second, outperformed by the EBP. In the last four columns (see *Statistics*), we report the average and standard deviations of the two metrics (ratio and rank) across the four dependent variables. The averages and standard deviations indicate that not only HY-NEIO produces the smallest RMSEs but it also has the lowest dispersion. For example, HY-NEIO has an average *Ratio* (*Rank*) of 0.877 (1.25) with a standard deviation of 0.06 (0.50), while EBP has an average *Ratio* (*Rank*) of 0.937 (3.25) with a standard deviation of 0.139 (2.22).

In Panel B of Table 7, we repeat the same out-of-sample exercise using multiple regression models. We use the first five variables as the benchmark model (i.e., *DEP*, DS, TS, TB, and DY). We then independently include HY-NEIO, HYS and EBP to the model and examine their forecasting performance. As in the univariate case, we find that HY-NEIO tends to produce the smallest RMSE in particular for one- and two-year future GDP growth and two-year future unemployment rate changes. Overall, Table 7 results show that HY-NEIO presents strong out-of-sample predictability.

5. The Fast-Moving and Smart-Money Behaviors of HY-NEIO

The previous results show that intra-family flow shifts into HY bond funds can serve as an early indicator for credit and economic cycles. Without knowing more about the identity of investors in HY funds, it is difficult to argue for a story in which these investors simply can forecast better than any other investors in the economy. Rather, our interpretation is that HY-NEIO provides an early signal of demand changes or changes in risk appetite, since it captures information on the first changes in asset allocation of high-yield debt investors. As such, investor flow shifts into high-yield funds can exhibit a "smart-money" behavior in that a trading strategy based on the signal from HY-NEIO can be highly profitable.

In this section, we first provide evidence that supports the idea that flow shifts captured by HY-NEIO are fast-moving money, which is informative of future aggregate investor demand captured by slow-moving total net flows. Next, we show that HY-NEIO also behaves similar to "smart" money, which can predict both the stock and bond market returns and a trading strategy based on the signal from HY-NEIO is highly profitable. Lastly, we show evidence consistent with the idea that the predicting power of HY-NEIO is due to its predicting power for future investor demand.

5.1. HY-NEIO as an Early Signal for Future Investor Demand

In Table 8, we ask whether HY-NEIO provides an early signal for investor demand changes represented by total net flows. Specifically, we examine the extent to which HY-NEIO can predict other flow components (i.e., NEIO and NSR) into various asset classes (i.e., EQ, IG, HY, and GM) using regressions of each of these future flow components on the other flow components.

Panel A of Table 8 provides results from the regression of the HY and IG flow components. The results show that HY-NEIO positively predicts flow components of both the HY and IG categories, consistent with the idea that HY-NEIO is an early demand component. Across all the columns from 1 through 8, the coefficient estimates on HY-NEIO are positive and statistically significant at the 5% level, thus showing that an increase in HY-NEIO leads to future increases in HY-NEIO, HY-NSAR, IG-NEIO, and IG-NSR over the next four quarters. The results are not driven by trend chasing in flows that might drive both HY-NEIO and contemporaneous bond returns, as we control for cumulative returns of each asset class. In contrast, we find surprising results that none of the other flow components, including past bond returns, can positively predict HY-NEIO, as shown in Columns 1 and 5. Interestingly, HY-NSR marginally predicts future HY-NEIO but with a negative sign (see Column 5). These results confirm that, across the four flow variables, HY-NEIO is an early predictor for the other flow components.

In Panels B and C of Table 8, we also examine whether HY-NEIO can predict flow components to the EQ and GM categories. Similar to the results in Panel A, we consistently find that HY-NEIO positively predict all other flow variables for both the EQ and GM categories, as can be seen from positive and statistically significant coefficients on HY-NEIO in Columns 2-4 and 6-8 in Panels B and C. In contrast, none of the other flow components can positively predict HY-NEIO in Columns 1 and 5. In sum, the findings in Table 8 support our view that HY-NEIO better captures early shifts in investor demand, that is, high-yield investors move first before other investors in the market come in, suggesting that HY-NEIO moves before the herd.

These results suggest that HY-NEIO is a very informative reflection of the demand shock that ignites credit cycles. Note also that HY-NEIO is a small component and so it is implausible to think that it is affecting the economic cycles directly. The high-yield corporate bond category accounts for only approximately 2% of total mutual fund assets. Moreover, the dollar amounts in high-yield intra-family flow shifts (i.e., exchanges in and out) are only around 30% of total net flows in the high-yield category.

5.2. The Smart-Money Behavior of HY-NEIO

If HY-NEIO captures early shifts in demand, we would expect HY-NEIO to positively predict returns. In Tables 9 and 10, we examine the predicting power of HY-NEIO for future stock and bond market returns in comparison with existing return predictors and other flow components. Based on predictability results, we then examine the performance of a trading strategy using signals from HY-NEIO.

Table 9 provides the results from the regression of future one- and four-quarter excess stock market returns on HY-NEIO, EQ-NEIO (intra-family flow shifts in EQ funds), EBP, HYS, and other control variables including TS, DS, TB, DY, and lagged returns of both the stock market and high-yield bond index. The results show that HY-NEIO positively predicts future stock market returns up to the next four quarters, as shown by positive and statistically and economically significant coefficient estimates across all specifications from Columns 1 through 6. For example, in Column 6, a one-standard-deviation increase in HY-NEIO is associated with a 5-6% increase in excess market returns. In comparison, EQ-NEIO negatively predicts the first quarter returns, as shown in Column 1, but it shows no predicting ability for longer horizons, which is consistent with the results provided in Ben-Rephael, Kandel, and Wohl (2012) who argue that EQ-NEIO captures short-term investor sentiment.[12] Thus, the results show strong predictability of stock market returns using HY-NEIO, whereas flow shifts to equity funds are followed by subsequent reversal in returns.

In Table 10, we examine whether HY-NEIO can predict bond index returns over up to the next four quarters. In particular, we consider both HY-NEIO and HY-NSR to highlight the differential predicting power of intra-family flow shifts and sales and redemptions. Columns 1 and 2 indicate that HY-NEIO positively predicts future bond market returns up to the next 2 quarters. In contrast, HY-NSR shows no signs of predicting power for future bond returns. In fact, an increase in HY-NSR is followed by a significant return reversal for the next four quarters, as shown in Column 6. This result is consistent with those in Greenwood and Hanson (2013) who show that an increase in the HYS is followed by lower bond returns for the next few years, to the extent that both HY-NSR and the HYS proxy for investor demand or sentiment in the credit markets.

In untabulated results, we construct a monthly trading strategy that invests in the Barclays HY corporate bond index based on HY-NEIO and compare its Sharpe ratio with a buy-and-hold strategy that invests a 100% in the HY corporate bond index. In particular, the return on the strategy based on HY-NEIO is calculated as $R_{t+1} = (1 + H_t) \cdot R_{HY,t+1} + (-H_t) \cdot R_{F,t}$, where H_t is a standardized HY-NEIO at time *t* with a mean of zero and a standard deviation of one, $R_{HY,t+1}$ is the return on the Barclays HY index, and $R_{F,t}$ is a one-month Treasury bill rate. For our sample

[12]Ben-Rephael, Kandel and Wohl (2012) provide evidence that equity flows are dumb. That is, quarterly EQ-NEIO is followed by a short-term stock market reversal.

period, we find that the annualized Sharpe ratio of this strategy is 1.00, whereas the annualized Sharpe ratio of the buy-and-hold strategy is only 0.63.

Note that our results do not necessarily run counter to the common perception based on equity mutual fund studies that fund flows represent “dumb-money” (e.g., Frazzini and Lamont 2008, and Lou 2012). At the same time, there is a growing literature that suggests that trading decisions by individual investors can carry valuable information (e.g., Kaniel, Saar and Titman 2008; Kelley and Tetlcok 2013, 2017). More importantly, unlike total net flows employed in previous studies, which are inertial and trend-chasing (e.g., Ippolito 1992, Chevalier and Ellison 1997, and Sirri and Tufano 1998), intra-family flow shifts are active portfolio decisions. Also, the investor base in high-yield funds is distinctly different from the investor base in equity funds. In particular, HY investors tend to be wealthier and more sophisticated, compared with equity mutual fund investors.[13,14] Thus, portfolio choices in HY investors could be a good signal for future investor flows and serve as an early indication of future demand changes.

5.3 Predicting Power of Intra-Family Flow Shifts and Future Total Net Flows

In Table 11, we examine the extent to which the predicting power of HY-NEIO operates through its predicting power for total net flows by regressing future credit and economic cycle variables on both HY-NEIO and *future* total net flows. If HY-NEIO predicts future economic and credit cycles through its informativeness in future investor demand, HY-NEIO is not expected to have predicting power after controlling for future total net flows. In contrast, if the forecasting power of HY-NEIO is not affected by future total net flows, then HY-NEIO may have additional information on future credit and economic cycles that is not captured by future aggregate investor demand.

[13] 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). Moreover, 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.

[14] From our detailed conversations with one of the largest asset managers in the U.S., they also confirm that investor pools are quite different and relatively higher concentration of wealthy and active investors in high-yield bond funds. Also, transaction costs in high-yield corporate bonds are particularly high for retail investors (Edwards, Harris, and Piwowar, 2007), which incentivize active investors to invest in mutual funds instead of trading within their own accounts.

Table 11 provides the estimation results from the regressions of the future HYS, HY spreads, stock market returns, changes in GDP growth, and changes in unemployment rates on current HY-NEIO and future total net flows. Our results overall show that future flows tend to absorb the predicting ability of HY-NEIO. In Columns 1 and 2, we have some evidence that HY-NEIO has information on the future HYS that is orthogonal to the information content in future fund flows, as can be seen from positive and statistically significant coefficients on HY-NEIO. In Columns 3 through 10, however, we find that future flows tend to absorb the explanatory power of HY-NEIO. In Columns 3 and 4, for example, HY-NEIO is no longer statistically significant at the conventional level, whereas future total net flows are highly statistically significant in explaining HY spreads, suggesting that investor demand, as proxied by total net flows, drives HY corporate bond prices. In the other Columns from 5 to 10, we find similar results.

5.4 What Explains HY-NEIO?

Recent literature attributes overheating in credit markets to investors' sentiment (see Greenwood and Hanson, 2013; Greenwood, Hanson, and Jin, 2016; Bordalo, Gennaioli, and Shleifer, 2016; and Lopez-Salido, Stein, and Zakrajšek, 2017). In particular, Bordalo, Gennaioli, and Shleifer (2016) sentiment builds on a notion of extrapolative beliefs in which investors condition on recent good outcomes to believe that future outcomes will also be good. In comparison, the demand shock that we capture with the HY-NEIO measure is different in the sense that the behavior of investors that is captured by HY-NEIO anticipates the cycle rather than follows it. The demand shock reflected in mutual funds portfolio shifts might ignite future credit overheating, while the behavior of indicators such as HYS might follow the shock.

In Table 12, we examine which factors, including credit sentiment indicators, can explain future HY-NEIO, thus shedding light on the lead-lag relations between HY-NEIO and credit overheating. In particular, we regress future HY-NEIO on HYS, returns on the high-yield bond index, and VIX as well as other common variables in the literature that might explain investor portfolio choices.[15]

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

Table 12 shows the regression results. We find that HY-NEIO does not tend to follow credit sentiment variables. In all the columns, HY-NEIO does not respond to past bond returns, showing that HY-NEIO is not driven by a feedback response in the credit market. We further find that HYS negatively (not positively) predicts HY-NEIO, consistent with the impulse response plotted in Figure 2, which suggests that overheating in credit conditions does not lead HY-NEIO. In other words, when HYS is elevated, investors in high-yield bond shift their money to other asset classes. Similarly, GDP growth (unemployment rate change) negatively (positively) predicts HY-NEIO, and thus investor shifts into high-yield bond funds occur during economic busts, not during booms. Interestingly, HY-NEIO negatively responds to changes in monetary policy. Thus, when the Federal Reserve increases rates to prevent market overheating, HY-NEIO responds by shifting money out of HY funds. Finally, we find that past stock returns and changes in VIX predicts future HY-NEIO, but the signs of coefficients imply that investors tend to shift to HY funds when market conditions are in general poor (i.e., low stock returns and increases in VIX).

Thus, Table 12 shows that HY-NEIO does not positively (negatively) respond to past positive (negative) economic and credit conditions. In this sense, demand shocks that we capture with HY-NEIO are very different from the sentiment described for example, in Greenwood and Hanson (2013) and Bordalo, Gennaioli, and Shleifer (2016). In fact, the investor behavior that is captured by HY-NEIO seems to anticipate the cycle rather than follows it. Consistent with our interpretation of HY-NEIO as an early demand shocks, HY portfolio shifts seems to be what gets the cycle started.

6. Extensions and Robustness Checks

6.1 Where Do Intra-Family Shifts to High Yield Come From?

By construction, the dollar amounts of flow shifts into high-yield bonds should be offset by flow shifts out of the other asset classes. In this section, we decompose HY-NEIO based into its flow sources to examine whether flow shifts out of a particular asset class drives the predicting power of HY-NEIO. This analysis will further help understand the source of HY-NEIO predictability.

To this end, we categorize asset classes into five asset classes: investment-grade (IG) bonds, hihgh-yield (HY) bonds, equity (EQ), government bonds and money market funds (GM), and other asset classes (O). Thus, we have:

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

By dividing total assets in the high-yield category, we can then rewrite net changes in high yields (HY-NEIO) 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 HY-NEIO originates from. In particular, we regress the future credit and business cycle variables on these four components of HY-NEIO.

Panel A of Appendix E presents results from the regressions of future credit and business cycle variables on the four HY-NEIO decompositions. We make the following two observations. First, it is difficult to conclude that any one of the four components is a dominant predictor. There are some cases where one variable is statistically significant over the other, but there is no consistent pattern across specifications. Second, the coefficients are all in the same signs and the economic magnitudes seem similar, and these coefficients are not statistically different from each other. 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.

6.2 Robustness Check: Horserace Between HY-NEIO and Flow Components in Other Asset Classes

As a robustness check on the predicting power of HY-NEIO for future credit and economic fluctuations, we run a horserace among HY-NEIO, EQ-NEIO, IG-NEIO, and GM-NEIO. Panel B of Appendix E reports the results. Across all specifications (Columns 1 through 8), we find that

HY-NEIO is statistically significant at the 5% level in predicting future economic and credit cycle variables even after controlling for the other NEIO variables and control variables. In contrast, the other NEIO variables, e.g., EQ-NEIO and GM-NEIO are not statistically significant at the 5% level in any of the columns. The only exception is IG-NEIO 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 HY-NEIO beats within-family flows to other asset classes, consistent with HY-NEIO being an early demand component.

In Appendix F, we further examine a horserace between HY-NEIO and NSR components into other asset classes. Panel A shows that HY-NSR does not predict many of the credit cycle variables that HY-NEIO can predict. In Columns 1 through 6, for example, HY-NSR is not statistically significant at conventional levels, while HY-NEIO is. In contrast, in Columns 7 and 8, HY-NSR exhibits strong predicting power for future economic cycle variables over the next year, i.e., changes in real GDP growth and unemployment rates. This stems from the fact that GDP and unemployment rate changes can be predicted over longer horizons (Table 5), and the fact that HY-NSR is more than double in magnitude relative to HY-NEIO. Taking into account the fact that HY-NEIO predicts HY-NSR (Table 8), in Appendix D, we include both HY-NEIO and HY-NSR in a VAR and allow a shock in HY-NEIO to affect HY-NSR. The impulse response functions show that a 1 standard deviation shock in HY-NEIO has a positive (negative) and significant effect on GDP (unemployment rate) while HY-NSR is neither economically nor statistically significant.

Finally, Panel B shows that controlling for NSR components in other asset classes does not diminishes the statistical significance of the coefficient estimates on HY-NEIO.

6.3 Robustness Check: The Predictive Power of HY-NEIO in Rolling Subsamples

The high-yield corporate bond mutual fund category has grown substantially over time, and is around 250 billion dollars in assets under management in the last year of our sample. On one hand, this increase could strengthen HY-NEIO predictive ability. On the other hand, an increase in popularity of the high-yield category could have a negative effect if it also attracts less sophisticated groups of investors. To examine whether a trend exists or not, we analyze HY-NEIO's predictive ability 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 HY-NEIO controlling for other variables. Figure 8 plots the regression coefficients. In general, we document that HY-NEIO predictive ability, measured by the coefficient estimates, has increased over time. Thus, is seems that the increase in AUM did not have a negative effect on HY-NEIO predictive ability.

6.4 Robustness Check: Using Flow Changes Instead of Flow Levels

Net-exchanges capture active asset allocation decisions, since investors shift existing money across asset classes. Net flows on the other hand, are affected by saving and withdrawal decisions. Interestingly, focusing on changes in flows, instead of flows, could potentially capture changes in investment rates, which could serve as a proxy for asset allocation decisions. For example, suppose that on aggregate mutual fund investors invest 5% of their monthly allocation in the high-yield mutual fund category. If suddenly they decide to allocate only 3% of their monthly deposits, this would be pick up as a -2% change using changes in flows. We repeat our main analysis using changes in HY flows instead of HY-NEIO. In an untabulated set of results, we find that while changes in flows are able to predict credit cycle variables to some degree, they are not able to predict business cycle variables. This shows that HY-NEIO is distinct from a simple measure of changes in investment rates and thus, carries valuable information.

7. Conclusion

The literature on credit and business cycles contains many studies exploring what predicts these cycles (e.g., Gilchrist and Zakrajšek 2012 and López-Salido, Stein, and Zakrajšek 2017). Recently, there is a developing narrative where investors' demand is a key driver in the fluctuations in credit markets and future economic activities. In this paper, we offer a direct measure of investor demand using investors' portfolio choices in high-yield bond funds, which can serve as a leading indicator for both credit and business cycles. Our measure thus captures early shifts in investors' demand towards high-risk credit, which predict the entire cycle.

In particular, our measure 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). In addition, it predicts growth in financial intermediaries' balance sheets and net amounts of total bond issuance. Our measure is also able to predict various credit spreads such as the high-yield, the default credit spreads and Gilchrist and Zakrajšek's (2012) excess bond premium (EBP). Consistent with these findings, our measure is able to positively (negatively) predict GDP growth (unemployment rates) earlier than other leading indicators in the literature, such as EBP. It also forecasts changes in monetary policy.

Positioning our measure in the timeline of the credit and business cycle (as described in Lopez-Salido, Stein, and Zakrajšek, 2017), our measure shows up a year in advance before an onset of a cycle. Thus, it provides early signs about the evolution of a cycle, which should be taken into consideration by policymakers. It also supports the idea that investors' demand is key in understanding these cycles.

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Table 1. Summary Statistics of Flow Components Across Asset Classes

This table reports summary statistics and correlation matrices for *NEIO* (normalized exchanges-in minus exchanges-out) and *NSR* (normalized sales minus redemptions) in the following asset classes: high-yield (HY) corporate bond mutual funds, investment-grade (IG) corporate bond mutual funds, equity (EQ) mutual funds, and government and money market (GM) mutual funds. The data are 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). Panel A reports the averages, the average absolute values, and the standard deviations of each asset class flow component. Panel B1 reports the correlations between NEIO and NSR *within* each asset class. Panels B2 (B3) reports the correlations between NEIOs (NSRs) across asset classes.

Panel A. Summary Statistics

	Avg.	Avg. of Abs.	Stdev.
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 B1. Correlation Matrices (NEIO and NSR within Groups)

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

Panel B2. Correlation Matrices (NEIO across Groups)

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

Panel B3. Correlation Matrices (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 *HY-NEIO*

This table presents results of quarterly predictive time series regressions of the future high-yield share (HYS) and reaching for yield (RFY) on HY-NEIO and other explanatory variables. HYS (Columns 1-3) is the log of the high-yield share, which is defined as the dollar fraction of non-financial high-yield-rated debt issues. RFY (Columns 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, $RFY_{jt} = \Sigma w_{jt} y_{jt} / \Sigma \frac{1}{N} y_{jt}$, where weight w_{jt} is determined by amounts outstanding of bonds. We then take the average across rating categories to obtain the reaching for yield measure, RFY_t. We regress the dependent variables, HYS and *RFY*, measured over the four quarters, $q+1$ from $q+4$, on the lagged dependent variable ($DEP_{q\text{-}3:q}$); the term spread (*TS*), the difference between 10-year and 1-year Treasury yields; the default spread (*DS*), the difference between Baa and Aaa corporate bond yields from Moody's; the 3 months T-Bill rate (*TB*); and the dividend yield (*DY*) calculated using CRSP as the sum of all dividends divided by the market cap. We also control for excess returns on the high-yield bond index from Barclays and the EBP of Gilchrist and Zakrajšek (2012), which is the difference between total corporate bond spread and the spread component that is predicted by expected defaults. The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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.

	HYS q+1:q+4			*RFY q+1:q+4*		
	(1)	(2)	(3)	(4)	(5)	(6)
HY-NEIO 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)
HYS 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 the EBP

This table presents the results of quarterly predictive time series regressions of credit spreads and the excess bond premium (*EBP*) on *HY-NEIO* and other explanatory variables. Panel A reports the regressions of the high-yield spread (HY-Aaa), which is the yield difference between the high-yield corporate bond index from Barclays and Aaa-rated bonds, and the default spread (Baa-Aaa), the yield difference between Baa- and Aaa-rated bonds. The dependent variables are measured in the next year (*q+4*). The control variables are *HY-NEIO* for the past year (*HY-NEIO*), the lagged dependent variable (*Spread*), the term spread (*TS*), the 3-month T-bill rate (*TB*), the dividend yield (*DY*), the log high-yield share (*HYS*), the excess bond premium (*EBP*), and the excess return on the high-yield bond index for the past year (*HYRET*). Panel B reports the regressions of *EBP* for the next quarter (*q+1*) on the lagged *EBP*, *HY-NEIO*, the term spread (*TS*), the 3-month T-bill rate (*TB*), the dividend yield (*DY*), and the log high-yield share (*HYS*). Following Gilchrist and Zakrajšek (2012), we use the quarterly average of the monthly *EBP* (*AveEBP*). The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in September 2010. Standard errors are calculated using the Newey-West 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 HY-NEIO

	Spread q+4							
	HY-Aaa				*Baa-Aaa*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
HYS 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 HY-NEIO

	AveEBP q+1		
	(1)	(2)	(3)
HY-NEIO q	-0.0404	-0.0367	-0.0372
	(-2.19)	(-2.01)	(2.05)
AveEBP q	0.8356	0.8727	0.8629
	(9.38)	(9.09)	(8.90)
TS q		4.895	4.659
		(1.08)	(1.05)
TB q		4.741	4.562
		(1.59)	(1.55)
DY q		-8.697	-8.985
		(1.38)	(1.38)
HYS q-3:q			-0.019
			(0.46)
AdjRSQ	0.705	0.708	0.706

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

This table presents results of quarterly predictive time series regressions of growth in intermediary balance sheet assets (*ΔA/A)* and net bond issuance (*NBI*) on *HY-NEIO* and other explanatory variables. *ΔA/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. Intermediary balance sheet data are obtained from Table L.129 of the Federal Reserve Flow of Funds, following Adrian, 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. The explanatory variables are *HY-NEIO*, the lagged dependent variable (*DEP*), the term spread (*TS*), the default spread (*DS*), the 3-month T-bill rate (*TB*), the dividend yield, the log high-yield share (*HYS*), the excess bond premium (*EBP*), and the excess return on high-yield bond index for the past year (*HYRET*). The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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.

	dA/A q+1			*NBI q+1*		
	(1)	(2)	(3)	(4)	(5)	(6)
HY-NEIO 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)
HYS 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 *HY-NEIO*

This table presents results of quarterly predictive regressions of changes in real GDP growth and changes in unemployment rate on *HY-NEIO*. In Panel A, the dependent variable are changes in log real GDP (*GDP*) over the next four quarters in columns (1) through (4) and over the next eight quarters in columns (5) through (8). The explanatory variables are *HY-NEIO*, a change in log real GDP over the past four quarters (*GDP*), the term spread (*TS*), the default spread (*DS*), the T-bill rate (*TB*), the dividend yield (*DY*), the log high-yield share (*HYS*), the excess bond premium (*EBP*), and cumulative excess returns on the high-yield bond index over the past four quarters (*HYRET*). In Panel B, the dependent variable are changes in unemployment rate (*UR*) over the next four quarters in columns (1) through (4) and over the next eight quarters in columns (5) through (8). The explanatory variables are the same as those in Panel A. The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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.

Panel A – Changes in Real GDP on *HY-NEIO*

	GDP							
	q+1:q+4				*q+1:q+8*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
GDP 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)
HYS 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 *HY-NEIO*

	UR							
	q+1:q+4				*q+1:q+8*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO q-3:q	-0.143	-0.113	-0.089	-0.071	-0.258	-0.182	-0.147	-0.118
	(-4.14)	(-4.06)	(-3.94)	(-3.05)	(-4.67)	(-3.60)	(-3.74)	(-2.79)
UR q-3:q	0.456	0.426	0.286	0.305	0.399	0.588	0.292	0.324
	(4.06)	(2.73)	(1.74)	(1.98)	(2.88)	(3.47)	(1.90)	(2.01)
TS q		-15.062	-27.631	-25.756		-58.351	-87.911	-84.796
		(-1.75)	(-2.21)	(-2.28)		(-2.19)	(-2.73)	(-2.67)
DS q		67.254	-1.915	-10.238		4.606	-4.973	-18.808
		(1.64)	(-0.07)	(-0.40)		(1.03)	(-0.12)	(-0.41)
TB q		8.800	-4.533	-5.355		12.675	-14.360	-15.727
		(1.39)	(-0.56)	(-0.65)		(1.06)	(-0.97)	(-1.05)
DY q		-22.399	-2.699	0.992		-29.339	7.737	13.871
		(-1.21)	(-0.15)	(0.05)		(-1.00)	(0.30)	(0.51)
HYS q-3:q			-0.055	-0.038			-0.165	-0.137
			(-0.28)	(-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 *HY-NEIO*

This table presents results of quarterly predictive regressions of changes in monetary policy on *HY-NEIO* and other explanatory variables. Changes in monetary policy are measured using the Federal Reserve's discount rate (columns 1-4), the federal funds rate (columns 5-8), and Romer and Romer (2004) monetary policy shocks measure (columns 9-12). The dependent variables are measured over the next eight quarters (*q+1:q+8*) or over the future eight quarters skipping the next four quarters (*q+5:q+12*). The explanatory variables are *HY-NEIO*, the dependent variable (i.e., changes in monetary policy) measured over the past four quarters (*DEP*), the term spread (*TS*), the default spread (*DS*), the 3-month T-bill rate (*TB*), the dividend yield (*DY*), the log high-yield share, the excess bond premium (*EBP*), the cumulative excess return on the high-yield bond index over the past four quarters (*HYRET*), and lagged changes in log real GDP (*GDP*) and lagged changes in unemployment rate (*UR*). The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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.

	Discount Rate				*Fed Fund Rate*				*Romer &Romer*			
	q+1:q+8		*q+5:q+12*		*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)	(11)	(12)
HY-NEIO q-3:q	0.198	0.194	0.170	0.217	0.133	0.133	0.252	0.230	0.071	0.054	0.113	0.098
	(3.42)	(3.15)	(2.76)	(2.27)	(2.09)	(2.13)	(3.87)	(2.49)	(2.13)	(1.89)	(2.94)	(2.35)
DEP q-3:q	0.590	0.138	-0.348	-0.287	0.597	-0.052	-0.361	-0.518	0.083	-0.215	0.194	0.363
	(2.96)	(0.44)	(-1.75)	(-1.24)	(2.51)	(-0.20)	(-1.95)	(-2.19)	(0.43)	(-1.44)	(1.14)	(2.01)
TS q	114.108	71.955	98.752	103.499	135.404	67.297	87.374	74.250	-18.597	-5.597	26.421	29.169
	(2.50)	(1.11)	(2.92)	(2.78)	(3.01)	(1.10)	(2.84)	(1.87)	(-0.73)	(-0.33)	(1.07)	(1.29)
DS q	-6.910	-53.435	-65.622	-76.062	2.627	17.228	-53.101	-57.763	-202.176	-169.254	-8.754	-65.560
	(-0.08)	(-0.64)	(-0.95)	(-0.80)	(0.03)	(0.22)	(-0.82)	(-0.63)	(-2.53)	(-3.07)	(-0.13)	(-0.87)
TB q	-12.554	-58.345	-6.714	-16.997	-7.520	-62.470	-4.741	-17.571	-61.473	-46.052	-30.078	-29.748
	(-0.64)	(-2.01)	(-0.38)	(-0.58)	(-0.37)	(-2.27)	(-0.26)	(-0.56)	(-3.70)	(-4.02)	(-2.05)	(-1.98)
DY q	-6.442	114.990	-13.589	-31.760	-22.884	98.986	-16.090	-11.652	203.068	213.088	118.587	113.321
	(-0.12)	(2.40)	(-0.23)	(-0.54)	(-0.41)	(2.32)	(-0.29)	(-0.21)	(4.77)	(6.84)	(2.81)	(2.82)
HYS q-3:q		1.214		-0.450		1.015		0.056		0.722		-0.078
		(2.56)		(-0.81)		(2.40)		(0.09)		(2.74)		(-0.28)
EBP q		-0.168		0.827		-0.495		0.882		-0.328		0.503
		(-0.28)		(1.13)		(-0.93)		(1.17)		(-1.45)		(1.38)
HYRET q-3:q		-0.038		0.009		-0.024		0.029		-0.010		0.025
		(-2.09)		(0.39)		(-1.01)		(0.96)		(-1.32)		(1.26)
GDP q-3:q		26.268		-17.731		10.425		-20.131		-18.981		-7.630
		(1.08)		(-0.76)		(0.38)		(-0.75)		(-1.98)		(-0.41)
UR q-3:q		26.268		-0.853		-1.160		-1.039		-0.387		0.249
		(0.72)		(-2.30)		(-1.75)		(-2.33)		(-2.62)		(0.79)
AdjRSQ	0.447	0.642	0.546	0.579	0.397	0.649	0.550	0.591	0.697	0.822	0.679	0.719

Table 7. Out-of-Sample Performance

This table presents the results of root-mean-squared forecasting errors (RMSE) of one- or two-years-ahead changes in real GDP growth (*GDP*) and changes in unemployment rate (*UR*), using regression coefficients from 10-year rolling estimation windows. In each quarter *q*, we first estimate regression coefficients using past 10 years of observations of dependent and independent variables known at that time. Using the coefficient estimates and the explanatory variables known in quarter *q*, we forecast the dependent variables over the next one-year (*q+1:q+4*) and two-year (*q+1:q+8*) horizons. Panel A reports the RMSEs from univariate regression models in which we estimate rolling-window coefficients by regressing dependent variables on a single independent variable including the lagged dependent variable (*DEP*), *HY-NEIO*, *HYS*, *EBP*, and other variables (*DS*, *TS*, *TB* and *DY*) that are used as control variables in our predictive regressions. We also report the ratio (*Ratio*) of the RMSEs with respect to the RMSE of the benchmark model, which uses *DEP* as the sole predictor. *Rank* is the ranking of RMSEs. Panel B reports the RMSEs from multiple regression models in which we estimate rolling-window coefficients by regressing dependent variables on the lagged dependent variable (*DEP*), the control variables (*DS*, *TS*, *TB* and *DY*), and one of *HY-NEIO*, *HYS*, and *EBP*. We also report the ratios (Ratio) of RMSEs with respect to the benchmark model, which uses *DEP* and the control variables as predictors. The last four columns (*Statistics*) report the average (*Avg.*) and standard deviation (*Stdev.*) of *Ratio* and *Rank*. Due to EBP data availability, the forecasting sample includes 106 quarterly observations, which results in 66 out-of-sample forecasts.

Panel A – Univariate Regression Models

	GDP q+1:q+4			*GDP q+1:q+8*			*UR q+1:q+4*			*UR q+1:q+8*			*Statistics*			
Variables	RMSE	Ratio	Rank	RMSE	Ratio	Rank	RMSE	Ratio	Rank	RMSE	Ratio	Rank	Avg. Ratio	Stdev. Ratio	Avg. Rank	Stdev. Rank
DEP q-3:q	2.239	1.000	5	3.785	1.000	2	1.352	1.000	7	1.939	1.000	4	1.000		4.500	2.082
DS q	2.295	1.025	6	4.733	1.251	8	1.247	0.923	6	2.261	1.166	7	1.091	0.146	6.750	0.957
TS q	2.308	1.031	7	4.119	1.088	6	1.165	0.862	4	1.766	0.911	2	0.973	0.105	4.750	2.217
TB q	2.161	0.965	4	3.846	1.016	3	1.175	0.870	5	1.821	0.939	3	0.948	0.061	3.750	0.957
DY q	2.458	1.098	8	4.524	1.195	7	1.410	1.043	8	2.667	1.375	8	1.178	0.146	7.750	0.500
HY-NEIO q-3:q	1.987	0.888	1	3.488	0.922	1	1.067	0.789	2	1.762	0.909	1	0.877	0.060	1.250	0.500
HYS q-3:q	2.145	0.958	3	3.906	1.032	5	1.114	0.824	3	1.948	1.004	5	0.955	0.092	4.000	1.155
EBP q	2.067	0.923	2	3.880	1.025	4	1.008	0.746	1	2.043	1.054	6	0.937	0.139	3.250	2.217

Panel B – Multiple Regression Models

	GDP q+1:q+4			*GDP q+1:q+8*			*UR q+1:q+4*			*UR q+1:q+8*			*Statistics*			
Variables	RMSE	Ratio	Rank	RMSE	Ratio	Rank	RMSE	Ratio	Rank	RMSE	Ratio	Rank	Avg. Ratio	Stdev. Ratio	Avg. Rank	Stdev. Rank
DEP q-3:q + Cont.	2.969	1.000	2	5.154	1.000	2	1.798	1.000	3	2.334	1.000	2	1.000		2.250	0.500
HY-NEIO q-3:q	2.840	0.956	1	4.888	0.948	1	1.741	0.968	2	2.176	0.932	1	0.951	0.015	1.212	0.530
HYS q-3:q	3.229	1.087	4	5.783	1.122	3	1.868	1.039	3	2.571	1.102	3	1.088	0.035	3.250	0.500
EBP q	3.062	1.031	3	5.801	1.125	4	1.626	0.904	1	2.735	1.172	4	1.058	0.118	3.000	1.414

Table 8. Lead-Lag Relations among Flow Components of Various Asset Classes

This table presents the results of quarterly regressions of future *NEIO* and *NSR* flow components on their lags across various asset classes. Panel A reports the regressions of NEIO and NSR components to the high-yield (HY) and investment-grade (IG) categories, measured over the next two quarters (*q+1:q+2*) in columns (1) through (4) and the next four quarters (*q+1:q+4*) in columns (5) through (8), on their lags and past cumulative returns on high-yield bond index returns (HYRET) and Baa-rated bond index returns (Baa). Similar to Panel A, Panel B reports regressions of the NEIO and NSR components to the high-yield (HY) and equity (EQ) categories, controlling for the past cumulative returns on high-yield bond index returns (HYRET) and stock market return (EXRET). Panel C reports regressions of the NEIO and NSR components to the high-yield (HY) and government and money market mutual fund (GM) categories, controlling for the past cumulative returns on high-yield bond index returns (HYRET) and 3-month T-bill rate. The sample period is from 1984 to 2012. 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*			
	HY-NEIO	*HY-NSR*	*IG-NEIO*	*IG-NSR*	*HY-NEIO*	*HY-NSR*	*IG-NEIO*	*IG-NSR*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
HY-NSR 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)
IG-NEIO 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)
IG-NSR 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 EQ Categories

	q+1:q+2				*q+1:q+4*			
	HY-NEIO	*HY-NSR*	*EQ-NEIO*	*EQ-NSR*	*HY-NEIO*	*HY-NSR*	*EQ-NEIO*	*EQ-NSR*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
HY-NSR 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)
EQ-NEIO 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)
EQ-NSR 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)
HY-RET 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)
EX-RET 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 GM Categories

	q+1:q+2				*q+1:q+4*			
	HY-NEIO	*HY-NSR*	*GM-NEIO*	*GM-NSR*	*HY-NEIO*	*HY-NSR*	*GM-NEIO*	*GM-NSR*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
HY-NSR 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)
GM-NEIO 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)
GM-NSR 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)
HY-RET 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 9. Regression of Future Stock Market Return on *HY-NEIO*

This table presents results of quarterly predictive regressions of excess stock market returns on *HY-NEIO* and other explanatory variables. Columns (1) through (3) report the regressions of the market excess return over the next quarter and columns (4) through 96) report the regressions of the market excess return over the next four quarters. *HY-NEIO* is the net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. *EQ-NEIO* 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). We also control for market excess returns over the past four quarters, the excess returns on the high-yield bond index (*HYRET*), the term spread (*TS*), the default spread (*DS*), the 3-month T-bill rate (*TB*), the dividend yield (*DY*), the log high-yield share (*HYS*), and the excess bond premium (*EBP*). The row, *1 SD HY-NEIO*, shows the one-standard-deviation effect of *HY-NEIO* on the future market returns. The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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.

	q+1:q+1			*q+1:q+4*		
	(1)	(2)	(3)	(4)	(5)	(6)
EQ-NEIO q-3:q	-0.0098	-0.0057	-0.0054	-0.0129	0.0136	0.0188
	(-1.89)	(-1.03)	(-1.04)	(-0.71)	(0.58)	(0.91)
HY-NEIO q-3:q	0.0062	0.0080	0.0087	0.0192	0.0176	0.0193
	(2.95)	(3.10)	(3.42)	(2.28)	(2.37)	(2.43)
MktExRet q-3:q	-0.0495	-0.0966	-0.1576	-0.0948	-0.0949	-0.3396
	(-0.87)	(-1.91)	(-2.88)	(-0.72)	(-0.70)	(-1.98)
HYRET q-3:q	0.0008	0.0007	-0.0005	-0.0006	-0.0010	-0.0041
	(0.67)	(0.54)	(-0.30)	(-0.36)	(-0.62)	(-2.05)
TS q		-2.420	-1.501		-2.922	0.218
		(-2.16)	(-1.09)		(-1.14)	(0.06)
DS q		-5.282	0.105		-3.000	14.471
		(-2.02)	(0.03)		(-0.48)	(1.59)
TB q		-1.035	-0.302		-2.349	0.324
		(-1.75)	(-0.36)		(-1.34)	(0.11)
DY q		4.23	3.14		11.63	7.86
		(2.07)	(1.47)		(1.94)	(1.39)
HYS q-3:q			0.001			0.005
			(0.04)			(0.16)
EBP q			-0.075			-0.227
			(-3.80)			(-3.47)
1 SD HY-NEIO	1.97	2.54	2.77	6.14	5.62	6.15
AdjRSQ	0.050	0.079	0.155	0.078	0.147	0.331

Table 10. Regression of Bond Market Index Returns on *HY-NEIO versus HY-NSR*

This table presents results of quarterly predictive regressions of bond index returns. In columns (1) through (3), we regress excess bond index returns for the next quarter (*q+1*), the next two quarters (*q+1:q+2*), and the next four quarters (*q+1:q+4*) on *HY-NEIO* (denoted as *FLOW*). Similarly, in columns (4) through (6), we regress excess bond index returns on *HY-NSR* (denoted as *FLOW*). In the top panel (*HY Bond Returns*) we regress excess returns on the high-yield bond index from Barclays and in the bottom panel (*Average IG Bond Returns*) we regress average investment grade excess bond returns, calculated as the equal-weighted average of AAA, AA, A and BBB rated indices from Barclays. We also control for past 12-months cumulative excess returns for the high-yield index (*HYRET*) and for the average investment-grade index (*AveIGRET*). *Controls* include the term spread (*TS*), the default spread (*DS*), the 3-month T-bill rate (*TB*), the dividend yield (*DY*). The row, *1 SD*, reports the one-standard-deviation effect of *HY-NEIO* and *HY-NSR* on future bond index returns. The sample period starts from 1984. HY-NEIO data ends in December 2012. 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.

	HY-NEIO			HY-NSR		
	q+1:q+1	q+1:q+2	q+1:q+4	q+1:q+1	q+1:q+2	q+1:q+4
	(1)	(2)	(3)	(4)	(5)	(6)
HY Bond Returns						
FLOW	0.317	0.501	0.283	-0.012	-0.060	-0.191
	(2.10)	(1.95)	(0.55)	(-0.25)	(-0.77)	(-1.82)
HYRET	-0.014	-0.065	-0.125	0.043	0.059	0.021
	(-0.33)	(-0.93)	(-1.30)	(0.98)	(0.85)	(0.27)
1 SD	1.05	1.66	0.94	-0.15	-0.79	-2.51
Controls	YES	YES	YES	YES	YES	YES
AdjRSQ	0.150	0.272	0.426	0.125	0.249	0.450
Average IG Bond Returns						
FLOW	0.129	0.196	0.047	-0.013	-0.043	-0.153
	(1.81)	(1.77)	(0.23)	(-0.58)	(-1.14)	(-3.19)
AveIGRET	-0.059	-0.089	-0.158	-0.009	0.010	-0.010
	(-1.69)	(-1.46)	(-1.79)	(-0.23)	(0.17)	(-0.10)
1 SD	0.43	0.65	0.16	-0.18	-0.57	-2.01
Controls	YES	YES	YES	YES	YES	YES
AdjRSQ	0.105	0.215	0.410	0.094	0.213	0.471

Table 11. *HY-NEIO* and Flows during subsequent year

This table reports the quarterly regressions of log HYS (columns 1-2), the credit spread (columns 3-4), the market excess return (columns 5-6), the difference in log real GDP (columns 7-8), and the difference in unemployment rates (columns 9-10). The explanatory variables are HY-NEIO, future total net flows in the high-yield category (HY-FLOW), and future total net flows in the high-yield and equity categories (HY&EQ FLOW). *Controls* refers to full specification of each dependent variable. The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in September 2010.

	HYS q+1:q+4		*Spread q+4*		*ExRet q+1:q+4*		*GDP q+1:q+8*		*UR q+1:q+8*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HY-NEIO q-3:q	0.073	0.068	-0.103	-0.012	0.014	0.007	0.002	0.001	-0.096	-0.052
	(3.31)	(2.68)	(-1.13)	(-0.15)	(2.00)	(0.92)	(1.65)	(1.30)	(-1.94)	(-1.20)
HY-FLOW q+1:q+4	0.020		-0.061		0.004		0.000		-0.011	
	(5.12)		(-2.95)		(1.67)		(0.86)		(-0.84)	
HY&EQ FLOW q+1:q+4		0.013		-0.065		0.005		0.000		-0.021
		(3.53)		(-4.00)		(2.67)		(1.60)		(-2.79)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AdjRSQ	0.770	0.728	0.436	0.485	0.373	0.417	0.361	0.383	0.468	0.490

Table 12. What Explains HY-NEIO

This table presents results of quarterly predictive time series regressions of HY-NEIO measured over subsequent four quarters. HY-NEIO is the net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous month assets. $HYRET_{q\text{-}3:q}$ is Barclay's high-yield excess bond index return over the previous 4 quarters. $HYS_{q\text{-}3:q}$ is the natural logarithm of high yield share over the previous 4 quarters. $NBI_{q\text{-}3:q}$ 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. $dA/A_{q\text{-}3:q}$ 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*. $GDP_{q\text{-}3:q}$ is a change in log real GDP from end-of-quarter *q-4* to end-of-quarter *q*. $UR_{q\text{-}3:q}$ is the difference between the unemployment rate at the end-of-quarter *q* and end-of-quarter *q*-4. $Fed\text{-}DRC_{q\text{-}3:q}$ in the sum of the federal discount rate changes over the previous 4 quarters. $VIX_{q\text{-}3:q}$ is the difference between end-of-quarter *q* and *q*-4 VXO levels, where the VXO is based on the implied volatility of the S&P100 options, highly correlated with the VIX, and available from 1986. $ExRET_{q\text{-}3:q}$ is the cumulative excess return of the market index over the previous 4 quarters. The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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.

	HY-NEIO q+1:q+4								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(10)
HY-NEIO q-3:q	0.057	0.078	0.039	0.046	-0.016	-0.038	-0.100	-0.039	0.003
	(0.40)	(0.53)	(0.28)	(0.30)	(-0.11)	(-0.25)	(-0.62)	(-0.25)	(0.02)
HYRET q-3:q	0.022	-0.002	0.016	0.033	0.016	0.013	0.026	0.081	0.009
	(0.63)	(-0.07)	(0.43)	(0.85)	(0.50)	(0.40)	(0.66)	(0.88)	(0.24)
HYS 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)					
GDP q-3:q					-51.550				
					(-1.98)				
UR q-3:q						0.921			
						(1.96)			
Fed-DRC q-3:q							-7.123		
							(-1.71)		
ExRet q-3:q								-0.078	
								(-2.51)	
DiffVIX q-3:q									0.185
									(2.82)
AdjQSR	0.080	0.041	0.016	0.015	0.059	0.050	0.327	0.078	0.148

Figure 1. 12-month Moving Average of HY-NEIO

The figure plots the 12-month moving average of HY-NEIO from January 1985 to December 2012. HY-NEIO is net exchanges (exchanges-in minus exchanges-out) from high-yield corporate bond funds normalized by the end-of-previous month assets. The data are obtained from ICI from February 1984 to December 2012. The three light gray columns represent NBER recession periods. The dark gray columns represent the 1987 market crash, the Mexican Peso crisis in 1994, and the European sovereign debt crisis in early 2010.

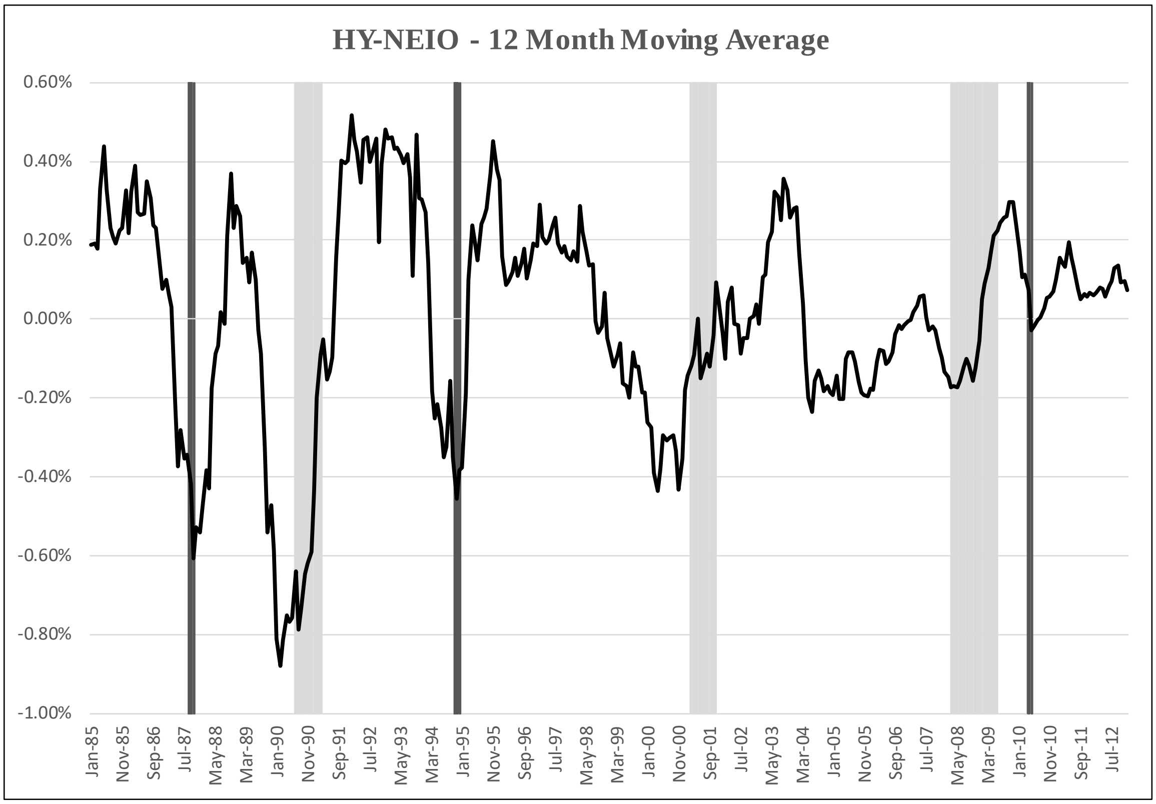


Figure 2. Impulse Response of HYS and HY-NEIO

This figure plots the impulse response of annual log of the high-yield share (*HYS*) and *HY-NEIO*. We estimate the following annual VAR (vector auto regression) system of *HYS* and *HY-NEIO* with 1 lag of each of the dependent variables:

$$HYS_y = \alpha_1 + \beta_1 HYS_{y-1} + \gamma_1 HY - NEIO_{y-1} + \varepsilon_{1y}$$
$$HY - NEIO_y = \alpha_2 + \beta_2 HYS_{y-1} + \gamma_2 HY - NEIO_{y-1} + \varepsilon_{2y}$$

The VAR includes 28 annual observations. Graphs a and b plot the cumulative response of *HYS* to a one-standard-deviation shock in *HY-NEIO* and *HY-NEIO* to a one-standard-deviation shock in *HYS*, 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) *HYS* to a 1 SD Shock in *HY-NEIO* **(b) *HY-NEIO* to a 1 SD Shock in *HYS***

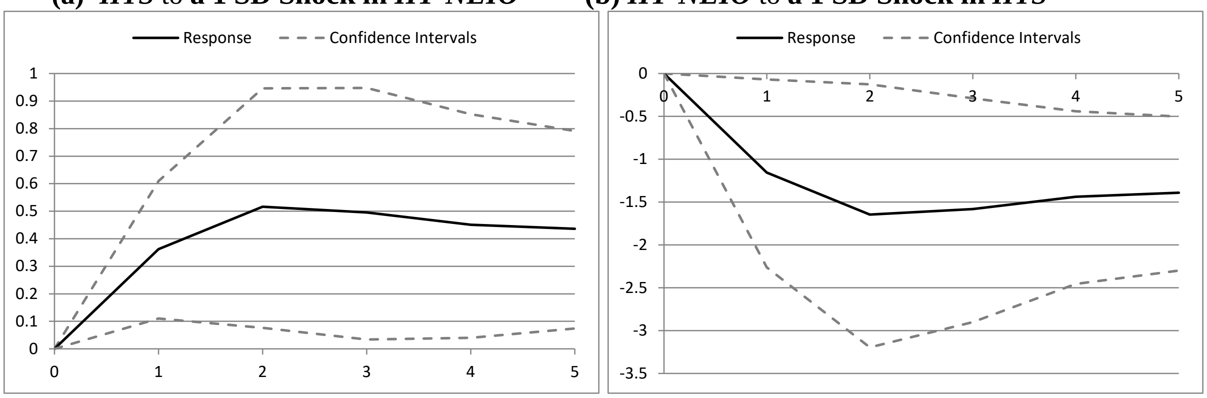


Figure 3. Impulse Response of HY Spread and HY-NEIO

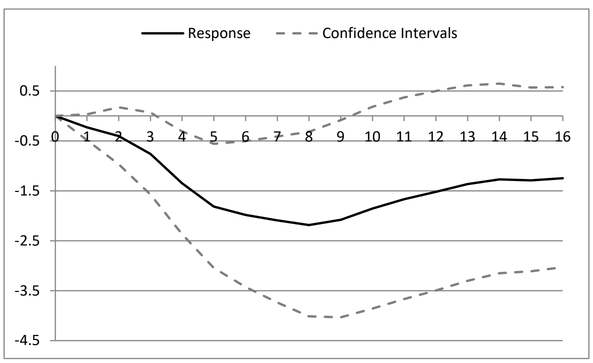
This figure plots the impulse response of quarterly HY-Aaa spread and *HY-NEIO*. We estimate the following quarterly VAR (vector auto regression) system of *HY-Aaa* and *HY-NEIO* with 8 lag of each of the dependent variables:

$$HY-Aaa_q = \alpha_1 + \sum_{t=1}^{8} \beta_{1i} HY-Aaa_{q-i} + \sum_{t=1}^{8} \gamma_{1i} HY-NEIO_{q-i} + \varepsilon_{1q}$$
$$HY-NEIO_q = \alpha_2 + \sum_{t=1}^{8} \beta_{2i} HY-Aaa_{q-i} + \sum_{t=1}^{8} \gamma_{2i} HY-NEIO_{q-i} + \varepsilon_{2q}$$

The VAR includes 115 quarterly observations, and we include lagged term spread (*TS*) and lagged 3-month T-bill rate (*TB*) as additional control variables. Graphs a and b plot the cumulative response of *HY-Aaa* to a one-standard-deviation shock in *HY-NEIO* and *HY-NEIO* 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 16 (marked as 16 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 *HY-NEIO* **(b) *HY-NEIO* to a 1 SD Shock in *HY-AAA***



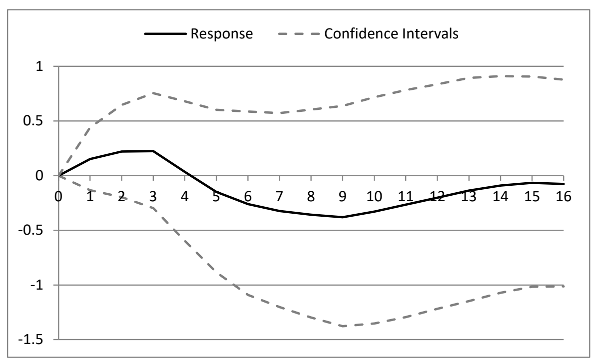


Figure 4. Impulse Response of Excess Bond Premium and *HY-NEIO*

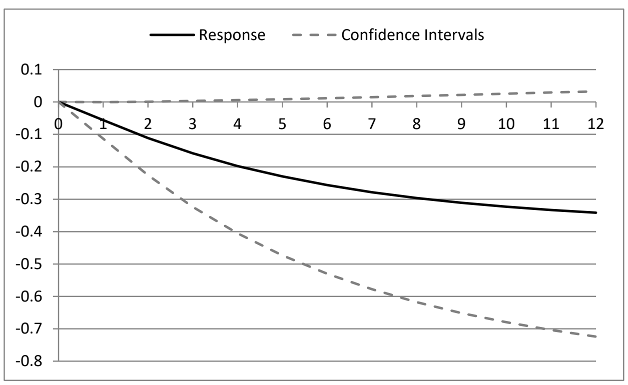
This figure plots the impulse response of quarterly excess bond premium and *HY-NEIO*. Excess bond premium (*AveEBP*) is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. We estimate the following quarterly VAR (vector auto regression) system of *AveEBP* and *HY-NEIO* with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

$$AveEBP_q = \alpha_1 + \beta_1 AveEBP_{q-1} + \gamma_1 HY - NEIO_{q-1} + \varepsilon_{1q}$$
$$HY - NEIO_q = \alpha_2 + \beta_2 AveEBP_{q-1} + \gamma_2 HY - NEIO_{q-1} + \varepsilon_{2q}$$

The VAR includes 106 quarterly observations, and we include lagged term spread (*TS*) and lagged 3-month T-bill rate (*TB*) as additional control variables. Graphs a and b plot the cumulative response of *AveEBP* to a one-standard-deviation shock in *HY-NEIO* and *HY-NEIO* 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 *HY-NEIO*



(b) *HY-NEIO* to a 1 SD Shock in *AveEBP*

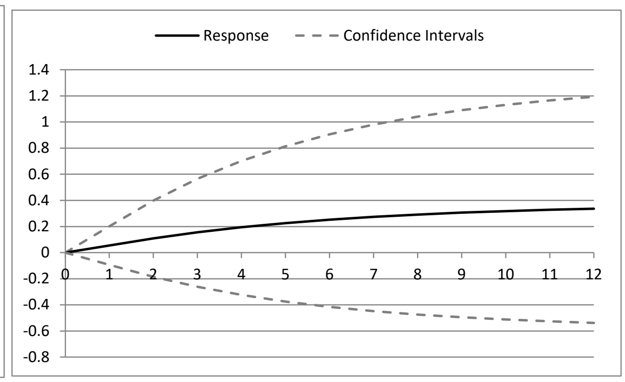


Figure 5. Impulse Response of Real GDP Changes to *HY-NEIO* and EBP

This figure plots the impulse response of quarterly changes in real GDP growth (*GDP*) to a one-standard-deviation shock in *HY-NEIO* and *EBP*, where *EBP q* is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. For comparison between HY-NEIO and AveEBP responses, AveEBP one-standard-deviation shock is multiplied by -1. We estimate the following quarterly VAR (vector auto regression) system of *GDP*, *HY-NEIO*, and excess bond premium with 8 lags of each of the dependent variables:

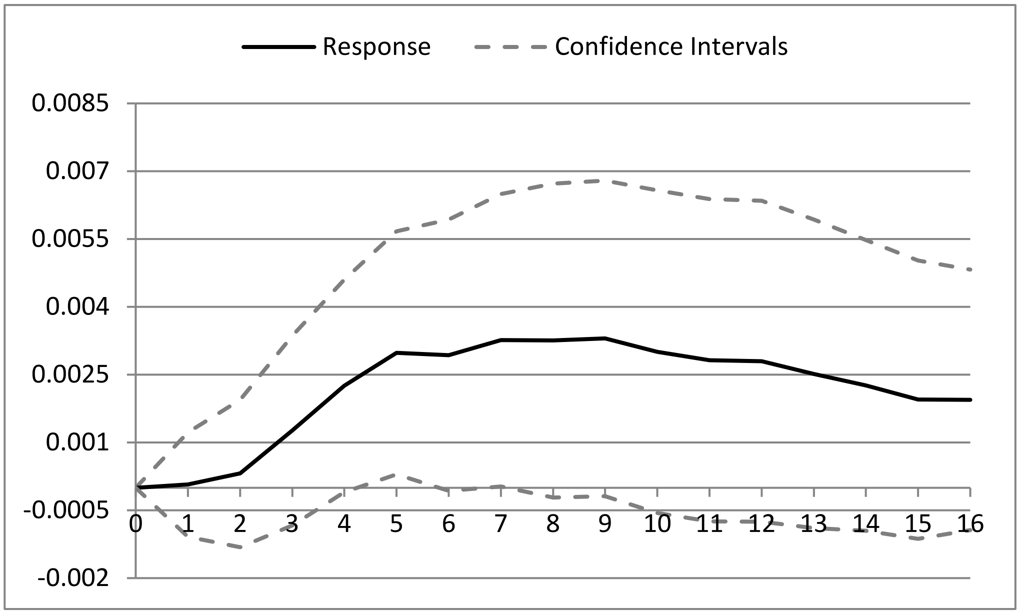
$$GDP_q = \alpha_1 + \sum_{t=1}^{8} \beta_{1i} GDP_{q-i} + \sum_{t=1}^{8} \gamma_{1i} HY - NEIO_{q-i} + \sum_{t=1}^{8} \delta_{1i} EBP_{q-i} + \varepsilon_{1q}$$

$$HY - NEIO_q = \alpha_2 + \sum_{t=1}^{8} \beta_{2i} GDP_{q-i} + \sum_{t=1}^{8} \gamma_{2i} HY - NEIO_{q-i} + \sum_{t=1}^{8} \delta_{2i} EBP_{q-i} + \varepsilon_{2q}$$

$$EBP_q = \alpha_3 + \sum_{t=1}^{8} \beta_{3i} GDP_{q-i} + \sum_{t=1}^{8} \gamma_{3i} HY - NEIO_{q-i} + \sum_{t=1}^{8} \delta_{3i} EBP_{q-i} + \varepsilon_{3q}$$

The VAR includes 106 quarterly observations, and we include lagged term spread (*TS*), lagged default spread (*DS*), and lagged 3-month T-bill rate (*TB*) as additional control variables. Graphs a and b plot the cumulative response of *GDP* to a one-standard-deviation shock in *HY-NEIO* 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).

(a) Cumulative Response to *HY-NEIO*



(b) Cumulative Response to *EBP*

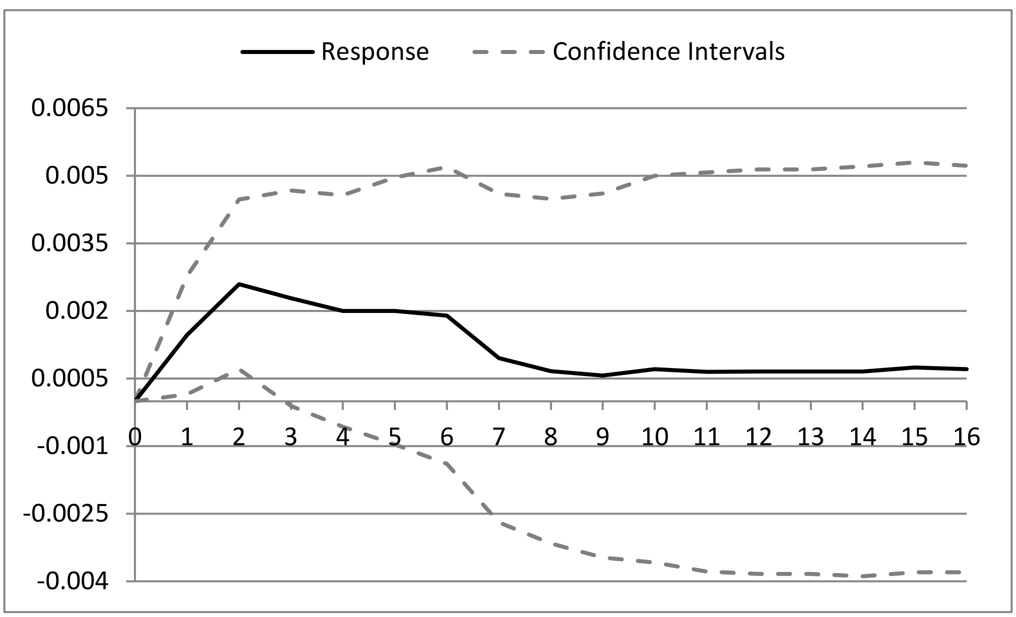


Figure 6. Impulse Response of Unemployment Changes to *HY-NEIO* and EBP

This figure plots the impulse response of quarterly changes in unemployment rates (*UR*) to a one-standard-deviation shock in *HY-NEIO* and *EBP*, where *EBP q* is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. For comparison between HY-NEIO 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 *UR*, *HY-NEIO*, and excess bond premium with 4 lags:

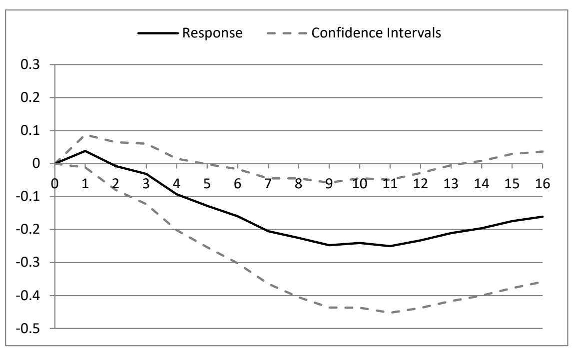
$$UR_q = \alpha_1 + \sum_{t=1}^{8} \beta_{1i} UR_{q-i} + \sum_{t=1}^{8} \gamma_{1i} HY - NEIO_{q-i} + \sum_{t=1}^{8} \delta_{1i} EBP_{q-i} + \varepsilon_{1q}$$

$$HY - NEIO_q = \alpha_2 + \sum_{t=1}^{8} \beta_{2i} UR_{q-i} + \sum_{t=1}^{8} \gamma_{2i} HY - NEIO_{q-i} + \sum_{t=1}^{8} \delta_{2i} EBP_{q-i} + \varepsilon_{2q}$$

$$EBP_q = \alpha_3 + \sum_{t=1}^{8} \beta_{3i} UR_{q-i} + \sum_{t=1}^{8} \gamma_{3i} HY - NEIO_{q-i} + \sum_{t=1}^{8} \delta_{3i} EBP_{q-i} + \varepsilon_{3q}$$

The VAR includes 106 quarterly observations, and we include lagged term spread (*TS*), lagged default spread (*DS*), and lagged 3-month T-bill rate (*TB*) as additional control variables. Graphs a and b plot the cumulative response of *UR* to a one-standard-deviation shock in *HY-NEIO* 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).

(a) Cumulative Response to *HY-NEIO*



(b) Cumulative Response to *EBP*

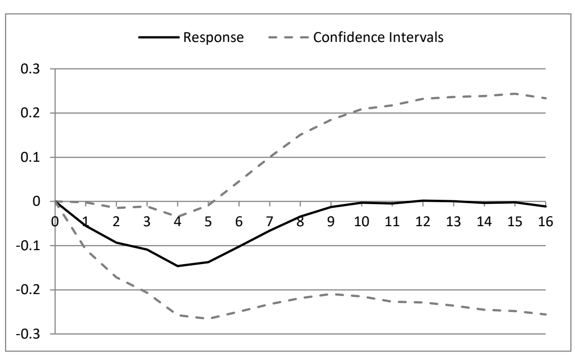


Figure 7. Timeline of Dynamics in Economic and Credit Cycle Indicators

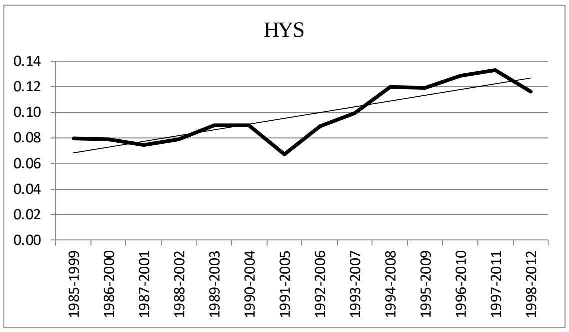
This figure depicts the timeline of HY-NEIO and existing indicators in the literature including high-yield share (HYS) and credit spreads with respect to GDP and growth and unemployment rates (UR).

t	***t* +1**	***t* +2**	***t* +3...**
HYNEIO +	High-Yield-Share +		
	Credit Spreads –	Credit Spreads –	Credit Spreads +
	GDP + / UER –	GDP + / UER –	GDP – / UER +
HYNEIO –	High-Yield-Share –		
	Credit Spreads +	Credit Spreads +	Credit Spreads –
	GDP – / UER +	GDP – / UER +	GDP + / UER –

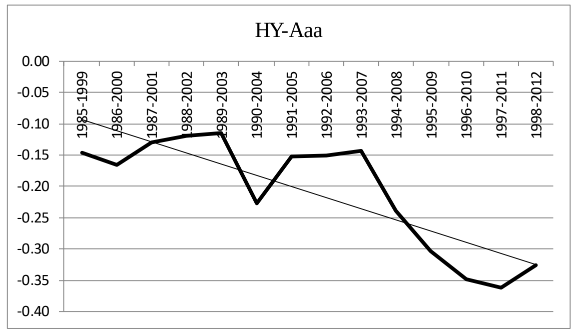
Figure 8. Trends in HY-NEIO Regression Coefficients

The figure plots regression coefficients from 15-year rolling windows for *HYS*, *HY-Aaa*, 1-year *GDP* and 1-year *UR*. The plots are based on the regression specification, which includes *HY-NEIO*, lag of the dependent variable, *TS*, *DS*, *TB* and *DY*.

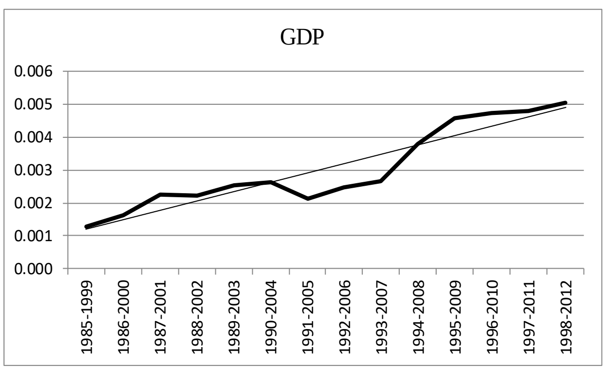
(a) HYS



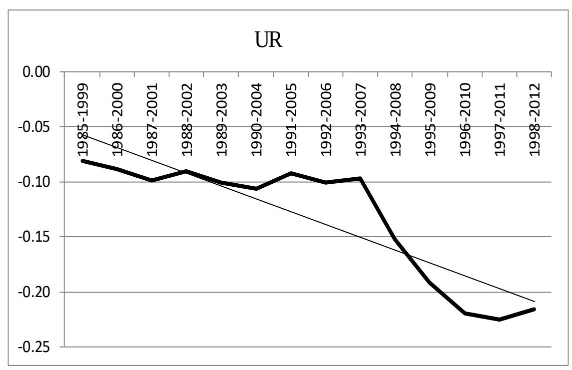
(b) HY-Aaa



(c) GDP



(d) UR



Appendix A. ICI Mutual Fund Categories

This appendix reports statistics for Investment Company Institute (ICI) 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 33 categories into five major asset classes: *Equity*, which includes both domestic and international mutual funds (categories 1-9); *Corporate Bond*, which includes both domestic and international corporate bond and balanced mutual funds (categories 10-22); *Municipal Bond*, which includes municipal bond funds (categories 23-26), *Government Bond*, which includes government bond funds (categories 27-29); and *Money Market*, which includes money market funds (categories 30-33). For each of the 33 categories, we report the number of monthly observations (*N*) and the average (*Avg*), median (*Median*) , minimum (*Min*), and maximum (*Max*) of fraction of assets in the category with respect to the total assets of all ICI categories.

			Category Assets / Total ICI Assets			
Asset Class	Category	N.	Avg	Median	Min	Max
Equity						
Aggressive Growth	1	347	5.7%	5.5%	2.8%	10.2%
Growth	2	347	11.9%	13.0%	5.7%	20.5%
Growth and Income	3	347	12.9%	12.7%	7.3%	19.3%
Income Equity	4	347	1.7%	1.6%	1.0%	2.9%
Sector	5	347	1.7%	1.9%	0.1%	3.8%
Emerging Markets	6	265	0.7%	0.4%	0.0%	2.1%
Global Equity	7	347	2.5%	2.7%	1.1%	4.3%
International Equity	8	347	3.4%	3.3%	0.3%	8.0%
Regional Equity	9	275	0.6%	0.5%	0.3%	1.2%
Corporate Bond						
Asset Allocation	10	275	0.5%	0.4%	0.2%	1.0%
Balanced	11	347	2.3%	2.4%	0.7%	3.2%
Flexible Portfolio	12	347	1.3%	1.6%	0.2%	2.3%
Income Mixed	13	347	1.6%	1.7%	0.6%	2.6%
Corporate - General	14	347	0.9%	0.9%	0.5%	1.4%
Global Bond - General	15	347	0.5%	0.4%	0.0%	1.4%
Strategic Income	16	347	3.4%	1.7%	0.6%	11.1%
World Bond	17	275	0.2%	0.1%	0.0%	0.9%
Corporate - Short Term	18	275	1.0%	0.9%	0.6%	1.7%
Corporate - Intermediate	19	275	0.9%	0.8%	0.6%	1.4%
Global Bond - Short Term	20	275	0.2%	0.1%	0.0%	1.4%
Mortgage Backed	21	347	2.0%	1.2%	0.5%	5.5%
High Yield	22	347	2.1%	2.0%	1.0%	4.1%
Muni Bond						
National Municipal Bond - General	23	347	3.6%	2.5%	1.6%	7.0%
State Municipal Bond - General	24	347	2.6%	2.2%	1.0%	5.4%
National Municipal Bond - Short Term	25	275	0.5%	0.5%	0.2%	1.1%
State Municipal Bond - Short Term	26	275	0.1%	0.1%	0.0%	0.3%
Government Bond						
Government Bond - General	27	347	2.6%	0.7%	0.3%	12.3%
Government Bond - Intermediate	28	275	0.6%	0.4%	0.2%	1.3%
Government Bond - Short Term	29	275	0.6%	0.4%	0.2%	2.2%
Money Market						
National Tax-Exempt Money Market	30	347	3.8%	2.8%	1.5%	8.7%
State Tax-Exempt Money Market	31	347	1.2%	1.3%	0.1%	2.3%
Taxable Money Market - Government	32	347	7.5%	6.9%	3.8%	16.1%
Taxable Money Market - Non-Government	33	347	20.2%	17.1%	11.1%	43.2%

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

This appendix provides an example of ICI flow data reported in millions of dollars for the HY corporate bond category during 1998. Net flows are broken down into four components: sales and redemptions (*Sales and Redem*), which are actual cash flows that enter or exit fund families and exchanges-in and exchanges-out (*Exch In and Exch Out*), which are transfers of existing cash flows across different asset classes within the same fund families. *SR* reports the net sales (sales minus redemptions) and *EIO* reports net exchanges (exchanges-in minus exchanges-out). Net flows (*Flow*) are the sum of the four components (sales, redemptions, exchanges-in, and exchanges-out). *Net Assets* is the category's net asset value at the end of the month.

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
Total		41,872	27,247	14,626	13,920	14,943	-1,023	13,602	

Appendix C. Wald Test for Impulse Response Differences

The appendix reports the cumulative impulse response functions of changes in real GDP growth (*GDP*) and changes in unemployment rate (*UR*) to a 1 standard deviation shock in HY-NEIO and EBP, together with the Wald tests for difference. Panel A reports the results for *GDP*, where Qtr 1-2, Qtr 3-9 and Qtr 10-15 stands for the cumulative impulse response during Quarters 1-2, 3-9, and 10-15, respectively. In a similar manner, Panel B reports the results for *UR*.

Panel A. GDP Growth

	Qtr 1-2	Qtr 3-9	Qtr 10-15
HY-NEIO Response	0.0003	0.0030	-0.0014
t-stat	(0.39)	(2.38)	(1.50)
EBP Response	0.0026	-0.0020	0.0002
t-stat	(3.56)	(-1.12)	(0.19)
Wald Test for Difference	-0.0023	0.0050	-0.0015
P-value	(0.03)	(0.01)	(0.30)

Panel B. Unemployment Rate

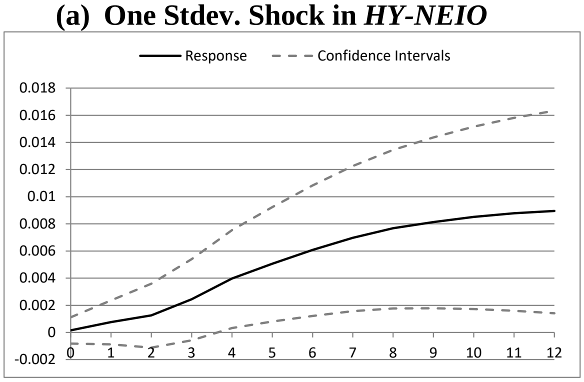
	Qtr 1-2	Qtr 3-11	Qtr 12-16
HY-NEIO Response	-0.0076	-0.2428	0.1076
t-stat	(-0.27)	(-2.62)	(1.35)
EBP Response	-0.0933	0.0887	-0.0156
t-stat	(-2.90)	(0.89)	(-0.18)
Wald Test for Difference	0.0857	-0.3316	0.1232
P-value	(0.04)	(0.02)	(0.34)

Appendix D. Impulse Response of Real GDP and Unemployment Rate Changes to 1 SD shock in *HY-NEIO and HY-NSR*

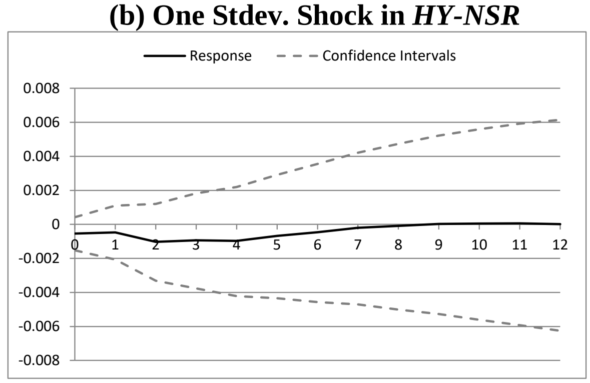
This appendix plots the cumulative impulse response of quarterly changes in real GDP growth (*GDP*) and quarterly changes in unemployment rate (*UR*) to a one-standard-deviation shock in *HY-NEIO,* and *HY-NSR.* In panel A we augment Figure 5's VAR analysis with HY-NSR as an additional independent variable. Thus, we estimate a quarterly VAR system of *GDP*, *HYNEIO*, *HYNSR* and *EBP* with 4 lags of each of the dependent variables. which allows us to capture the dynamics between *HY-NEIO* and *HY-NSR*. In panel B, we augment Figure 6's analysis and replace *GDP* with *UR*. The VAR includes 106 quarterly observations. To take into account the fact that HY-NEIO leads HYNSR (Table 9) and EPB (Table 3.B), we set the contemporaneous Cholesky shock order to *HY-NEIO*, *HY-NSR*, *EBP* and *GDP (UR)*. Graphs a and b (c and d) plot the cumulative impulse response of *GDP* (*UR)* to a one-standard-deviation shock in *HY-NEIO* and *HY-NSR*, 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 *GDP* to

(a) One Stdev. Shock in *HY-NEIO*

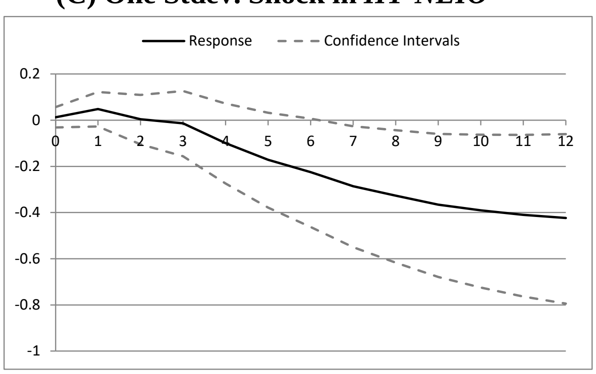


(b) One Stdev. Shock in *HY-NSR*

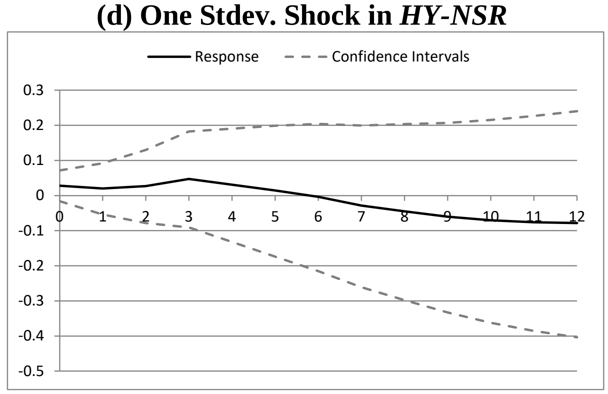


Cumulative Response of *UR* to

(C) One Stdev. Shock in *HY-NEIO*



(d) One Stdev. Shock in *HY-NSR*



Appendix E. *HY-NEIO* 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 *HY-NEIO* and other asset class *NEIO*s (Panel B). In Panel A, we decompose HY-NEIO 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 HY-NEIO as

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

= EQC+IGC+GMC+OC

where the suffix "C" stands for the relevant component. Using this decomposition, we examine where the predicting power of *HY-NEIO* 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). *Controls* refers to full specification of each dependent variable. The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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.

Panel A – Decomposing *HY-NEIO*

	HYS	*RFY*	*NBI*	*DA/A*	*HY-Aaa*	*MktExRet*	*GDP-1Y*	*UR-1Y*
	(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 *HY-NEIO* with other asset class *NEIO*s

	HYS	*RFY*	*NBI*	*DA/A*	*HY-Aaa*	*MktExRet*	*GDP-1Y*	*UR-1Y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
EQ-NEIO 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)
IG-NEIO 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)
GM-NEIO 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

Appendix F. *HY-NEIO* and Asset Class *NSR*s

In this table we extend our previous analyses by exploring the relation between *HY-NEIO* and *HY-NSR* (Panel A) and *HY-NEIO* and other asset class *NSRs* (Panel B). *Controls* refers to full specification of each dependent variable. The sample period starts from 1984. HY-NEIO data ends in December 2012. The EBP data ends in 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. Given the persistence in the NSR components, the coefficient estimates and standard errors are corrected using Amihud and Hurvich (2004) correction procedure.

Panel A – Contrasting *HY-NEIO* with *HY-NSR*

	HYS	*RFY*	*NBI*	*dA/A*	*HY-AAA*	*MktExRet*	*GDP-1Y*	*UR-1Y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
HY-NSR 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 – Contrasting *HY-NEIO* with other Asset Class *NSR*s

	HYS	*RFY*	*NBI*	*dA/A*	*HY-AAA*	*MktExRet*	*GDP-1Y*	*UR-1Y*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO 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)
EQ-NSR 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)
IG-NSR 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)
GM-NSR 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