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Mutual fund flows and fluctuations in credit and business cycles ☆

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ABSTRACT

Several measures of credit-market booms are known to precede downturns in real economic activity. We offer an early indicator for all known measures of credit booms. Our measure is based on intra-family flow shifts towards high-yield bond mutual funds. It predicts indicators such as growth in financial intermediary balance sheets, increase in shares of high-yield bond issuers, and downturns of various measures of credit spreads. It also directly predicts the business cycle by positively predicting GDP growth and negatively predicting unemployment. Our results provide support for the investor demand-based narrative of credit cycles and can be useful for policymakers.

1. Introduction

A large body of literature in macroeconomics and finance studies the link between credit markets and macroeconomic cycles. A pattern that emerges from the data is that credit booms precede downturns in macroeconomic activity.[1] This pattern attracts considerable attention from academics and policymakers: if credit markets are at the root of macroeconomic fluctuations, then it is important to better understand what drives credit cycles and identify leading indicators to try and design policies that will moderate them.

In this paper we show that investor portfolio choice toward high-yield corporate bond mutual funds is a strong predictor of all previously identified indicators of credit booms. An increase in our measure in year t predicts credit booms marked by the other indicators in the literature in years $t+1$ and $t+2$. These other indicators include the

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[1] See, for example, Schularick and Taylor (2012), Jorda et al. (2013), Mian et al. (2017), and López-Salido et al. (2017).

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proportion of low-quality bond issuers (Greenwood and Hanson, 2013; López-Salido et al., 2017), the degree of reaching for yield in the bond market (Becker and Ivashina, 2015), balance sheet growth in financial intermediaries (Schularick and Taylor, 2012; Krishnamurthy and Muir, 2015), and various measures of credit spreads (Gertler and Lown, 1999), in particular the excess bond premium (EBP) recently proposed by Gilchrist and Zakrajšek (2012). In addition, our measure, as a leading indicator of credit booms, positively predicts GDP growth and negatively predicts unemployment rates in years $t+1$ and $t+2$ (before they turn in the reverse direction in year $t+3$).

In building the relevant measure of investor choices for mutual funds, we wish to capture changes in investor demand for high-risk credit that show up prior to typical price- or quantity-based market variables. Mutual fund data generally have the potential to provide such information by revealing investor 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, *intra-family* and *high-yield*.

We focus on the *intra-family* component for two primary reasons. First, intra-family flow shifts are transfers of existing money across asset classes within a fund family and so they precisely reflect investor decisions whereby they allocate 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 exchange 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 investor demand for a particular asset will show up more quickly in intra-family flows.

There are also two reasons explaining our focus on shifts into *high-yield* bond funds. The vast literature on credit markets and business cycles has shown the importance of the high-yield segment of the credit market for detecting economic changes. For example, Gertler and Lown (1999) show that high-yield bond spreads serve as a leading indicator for economic cycles, which they attribute to the high sensitivity of firms in this segment to financial frictions. More recently, Greenwood and Hanson (2013) and also Lopez-Salido et al. (2017) show that financing activities of below-investment-grade firms have strong predictive power for future economic fluctuations, which they attribute to investor sentiment. Furthermore, intra-family flow shifts in the high-yield sector account for only a small fraction of the total fund flows in the broader sector, another advantage of using this variable as an early indicator.[3] In comparison, flows in and out of the broader mutual fund sector are themselves market-wide outcomes and will move contemporaneously with credit cycles rather than preceding them. Hence, investor portfolio shifts into the high-yield sector can provide a more useful barometer of economic conditions than flows into the broader asset categories.

We obtain our data on intra-family flow shifts from the Investment Company Institute (ICI). The 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 net exchanges (exchanges-in minus exchanges-out) for high-yield corporate bond funds (hereafter, HY-NEIO). For comparison, we also define HY-NSR, the net of the sales and redemption components in high-yield bond funds. HY-NSR accounts for a much larger portion of total net flows compared with HY-NEIO. We confirm 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. Furthermore, HY-NEIO is a fast mean-reverting process with its peaks and troughs preceding major market events, which implies that its statistical power for forecasting economic cycles will be strong even in a relatively short time series.

Let us now describe our results in greater detail. In a recent influential paper, Greenwood and Hanson (2013) show that the proportion of high-yield bond issuance, or the high-yield share (HYS), is an indicator of a credit boom that predicts an increase in the credit spread. They thus interpret HYS as an indicator of overheating. More recently, Lopez-Salido et al. (2017) show that the HYS can predict an upcoming macroeconomic downturn. Our first finding is that our indicator from mutual-fund flows, HY-NEIO, serves as 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 amount–weighted average of corporate bond yields divided by the simple average of the yields in each rating.[4]

In the next set of predictive regressions, we explore the ability of HY-NEIO to predict various indicators related to credit spreads. These include 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 indicators up to one year in advance, suggesting that when investors shift their portfolio compositions toward high-yield bonds, future bond

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

[3] Total assets under management in the high-yield sector comprise on average 2.1% of total assets in the broader mutual fund sector.

[4] This measure captures the relative fraction of higher-yielding corporate bonds in a given rating. See Choi and Kronlund (2018) for further details.

prices will be elevated and credit spreads will narrow. Another set of variables revolves around quantities of credit: We show that HY-NEIO predicts balance sheet growth in 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 financial sector growth with HY-NEIO is of high importance.

Next, we examine the forecasting power of HY-NEIO for future GDP growth and unemployment rate changes in comparison with the forecasting power of credit spreads and the EBP. To be a useful indicator beyond the existing predictors, our variable should be able to detect future booms and busts in 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 within a much shorter horizon. Second, in multiple regressions, HY-NEIO exhibits strong forecasting power for future GDP growth and changes in unemployment rates. Again, HY-NEIO can predict these variables much in advance of the other variables.

The results mentioned so far suggest that HY-NEIO may contain valuable information for policy and that it may be useful to include in 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 the tightening of future monetary policy, as measured by two-year changes in the Fed's discount rate, the actual Fed fund rate, and Romer and Romer's (2004) monetary policy shocks measure. HY-NEIO predicts these policy changes up to 12 months sooner than the previous indicators, the EBP and the HYS. In contrast, monetary policy changes do not predict future HY-NEIO. Furthermore, we also show that HY-NEIO is practically helpful in real-time forecasting. In out-of-sample tests of forecasting GDP growth and unemployment rate changes, employing HY-NEIO produces the lowest average and dispersion in root-mean-squared forecasting errors, compared with other leading indicators.

There are two key advantages of HY-NEIO as an indicator of the credit boom. First, it provides an early signal much in advance of all other indicators that have been linked to credit booms in previous literature. This is very useful to policymakers who are constantly looking for leading indicators. Second, it is linked directly to investors' flows, and so helps trace the origins of the credit boom to an increase in investors' demand. While papers by Greenwood and Hanson (2013) and Lopez-Salido et al. (2017) attribute overheating in credit markets to investors, they do not provide a clear proxy for changes in investor demand. Our HY-NEIO measure, being based on actual investors' flows, comes much closer to detecting changes in investor demand.

When thinking about the increased flow of investors into high-yield funds ahead of the credit boom, two possible interpretations come to mind. Our leading interpretation is that HY-NEIO provides an early indication of changes in appetite for risk on the part of debt investors. As we mentioned above, this measure is capable of detecting these changes early because it contains information about the first changes in investor asset allocation. This supports the idea that shocks to credit supply, triggered by investors' preferences or appetite for risk, are important drivers of the credit cycle. Consistent with this idea, when we decompose HY-NEIO into expected and unexpected components based on macroeconomic factors, we find that the predictive power of HY-NEIO is driven mostly by its unexpected component.

Another interpretation is that the investors, whose flows are captured by our measure, simply do a good job forecasting upcoming trends in the economy and trade profitably on these forecasts. Along these lines, we show that investors shifting their money into high-yield funds exhibit "smart-money" behavior: a trading strategy based on the signal from HY-NEIO is highly profitable, with an annual Sharpe Ratio of 1.00. However, without knowing more about the identity of investors in high-yield funds, this interpretation is more difficult to support, as it suggests that these investors are better than anyone else in the economy at projecting future economic developments. Instead, we think it is more plausible that these intra-family flows into high-yield funds provide early detection of changes in preferences or attitude to risk. Indeed, our results indicate that their profitability owes to the fact that they represent fast-moving money that is informative of future aggregate investor demand captured by slow-moving total net flows.[5]

Other than the papers about the credit cycle and its connection to the business cycle that we have mentioned so far, our paper is related to the vast literature that studies the ability of market prices to predict future economic activities. These studies include Fama (1981), Harvey (1988), Estrella and Hardouvelis (1991), Gertler and Lown (1999), Ang et al. (2006), Gilchrist et al. (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 a body of literature that uses fund flows 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 et al. (2012), who study the behavior of

[5] Note that the investors' demand shock we capture with the HY-NEIO measure is different from the sentiment described in the theoretical literature attributing credit cycles to behavioral explanations (e.g., Bordalo et al., 2017 and Greenwood et al., 2016). In these models, investors mistakenly take recent good outcomes to form beliefs that future outcomes will also be good, and this can cause amplification in credit cycles. However, the behavior of investors that is captured by HY-NEIO anticipates a cycle rather than follows it. It is of course possible that the extrapolative beliefs in these models or the financial frictions in the other theories of credit cycles (e.g., Bernanke and Gertler, 1989 and Kiyotaki and Moore, 1997) magnify a boom, but the demand shock reflected in HY-NEIO seems to be what starts it.

intra-family exchanges in and out of equity funds, using ICI data as we do. However, as we report, the behavior of these intra-family flows for equity funds differs considerably from 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 that of the relatively savvy investors in high-yield funds.

Finally, our paper is related to the recent literature that studies the behavior of investors in and managers of corporate bond funds, including papers by Feroli et al. (2014), Chen and Qin (2016), Goldstein et al. (2017), and Choi and Kronlund (2018). Corporate bond funds have grown dramatically in recent years and these studies are trying to assess their behavior, the extent to which they differ from equity funds, and the 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 variables. Section 3 describes results pertaining to the predictive power of high-yield intra-family flow shifts for key indicators of credit cycles. In Section 4, we use the high-yield intra-family flow shifts to predict the business cycle and monetary policy. Section 5 explores the fast-moving and "smart-money" behaviors of these shifts. In Section 6, we provide extensions and robustness tests. Section 7 concludes.

2. Data

2.1. Aggregate mutual fund flow data

Our aggregate fund flow data are obtained from the Investment Company Institute (ICI). The data period ranges from January 1984 through December 2018, a total of 420 months. The ICI classifies the data into 33 distinct investment categories, as reported in Appendix A.[6] 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 (GM) funds. The IG category includes pure (bond-only) and balanced (equity and bonds) funds investing in domestic and international markets.[7]

The ICI sorts fund 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 flows into two materially distinct parts: net sales (sales minus redemptions, or SR hereafter), which capture actual money that enters or exits 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 et al. (2012), SR captures mainly long-term savings and withdrawals, while EIO is purportedly driven by investors' asset allocation decisions.

Appendix B provides an example of the HY bond category during 1998, the period of the Russian default and the Long-Term Capital Management collapse. For that period, SR adds up to 14.63 billion dollars while the total EIO is negative, at −1.02 billion dollars. Even though investors shifted their capital away from the HY category, due possibly to increased risk in the market, total net flows into HY bonds were positive (13.6 billion dollars), driven by large SR (the abovementioned 14.63 billion dollars). This example shows that EIO should 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 EIO (NEIO) of the HY category in a given month, where normalization is based on the net assets of the category in the previous month, following an approach similar to that of Ben-Rephael et al. (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 SR (NSR) of the HY category. We also calculate NEIO and NSR 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 0.512%, showing increasing capital inflows into HY funds during the sample period, while average HY-NEIO is practically zero. The EQ, IG, and GM categories present similar patterns. In Panel B we report the monthly contemporaneous correlations of NEIO and NSR within and across asset classes. Panel B2 shows that HY-NEIO, IG-NEIO, and EQ-NEIO are all strongly and negatively correlated with GM-NEIO, indicating that net exchanges measure investor risk-taking behavior. In contrast, in Panel B3 correlations between NSR components are positive, showing that net flows across asset classes tend to co-move because they are driven mostly by investors' correlated saving decisions and capital inflows into the mutual fund sector. Overall, Table 1 suggests that NEIO is a cleaner signal for investor portfolio allocation choices than NSR.

In Fig. 1 we plot the 12-month moving averages of HY-NEIO. The figure showcases how our measure can be an

[6] The ICI also provides another version of the data based on a classification of 42 investment categories. Importantly, this classification is available only beginning in 2000.

[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.

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 the ICI and span from February 1984 through December 2018. The HY, IG, EQ, and GM asset classes are constructed using the ICI's categories 22, 10–17, 1–9, and 27–33, respectively (see Appendix A for more details). In Panel A we report the averages, the average absolute values, and the standard deviations of each asset class flow component. In Panel B1 we report the correlations between NEIO and NSR *within* each asset class. In Panels B2 and B3 we report the correlations between NEIOs (NSRs) *across* asset classes.

Panel A: Summary statistics

	Avg.	Avg. of Abs.	Stdev.
HY-NEIO	0.001	0.440	0.626
EQ-NEIO	−0.040	0.149	0.253
IG-NEIO	−0.014	0.124	0.176
GM-NEIO	0.029	0.162	0.239
HY-NSR	0.512	1.140	1.430
EQ-NSR	0.421	0.544	0.615
IG-NSR	0.738	0.849	0.923
GM-NSR	0.371	1.460	1.829

Panel B1: Correlation matrices (NEIO and NSR within groups)

	NSR			
NEIO	HY	EQ	IG	GM
HY	0.51			
EQ		0.33		
IG			0.33	
GM				0.04

Panel B2: Correlation matrices (NEIO across groups)

	NEIO		
NEIO	EQ	IG	GM
HY	0.32	0.34	−0.59
EQ		0.22	−0.78
IG			−0.42

Panel B3: Correlation matrices (NSR across groups)

	NSR		
NSR	EQ	IG	GM
HY	0.41	0.52	0.10
EQ		0.68	0.06
IG			0.03

early indicator of economic cycles with strong statistical power in a relatively short sample period. First, we observe large swings of HY-NEIO with relatively high-frequency cycles, showing that our measure is a quick, mean-reverting series. This time-series property contrasts with that of most other common predictors of credit cycles, such as interest rates or leverage, which tend to be highly persistent processes and thus require long sample periods to be useful for reliably estimating predictive regressions.[8]

In addition, the peaks and troughs of HY-NEIO precede not only the economic cycles but also some of the known major market events. For example, there are large troughs before the three NBER recessions. HY-NEIO also decreases significantly before major crisis and credit events, e.g., the 1987 market crash,[9] the Mexican Peso crisis of 1994, and the European sovereign debt crisis of early 2010.

3. Intra-family flow shifts and credit cycle fluctuations

In this section, we examine the extent to which HY-NEIO can predict leading indicators of credit cycles suggested in the prior literature. In particular, we focus on the following indicators: (1) the HYS of Greenwood and Hanson (2013), which measures the quality of corporate bond issuers and also credit-market sentiment according to Lopez-Salido et al. (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 been shown to have strong predictive power for future economic activities. In addition, we 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 of the severity of a financial crisis.

In all our analyses we control for variables that have previously been found to be important for 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), which is the sum of dividends for the previous 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 the HYS and the EBP, since both have been 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 of returns on corporate bonds. When credit markets are booming and thus risk premia are low, a larger fraction of junk-quality firms can issue corporate bonds, which in turn predicts lower corporate bond returns. Lopez-Salido et al. (2017) use the HYS as a proxy for credit market sentiment, which they show can predict future economic fluctuations.

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.

[8] Lopez-Salido et al. (2017) also point out that credit sentiment tends to have a much shorter half-life than those of balance-sheet-based measures of credit cycles.

[9] One might wonder whether the 1987 crash was a surprise event and was not likely to have been predicted. Rather, our view is that HY-NEIO predicted the jittery market conditions prior to the months leading up to the crash. See, for example, the *Wall Street Journal* article on January 19, 1987: "Raging bull, stock market's surge is puzzling investors; When will it end?"

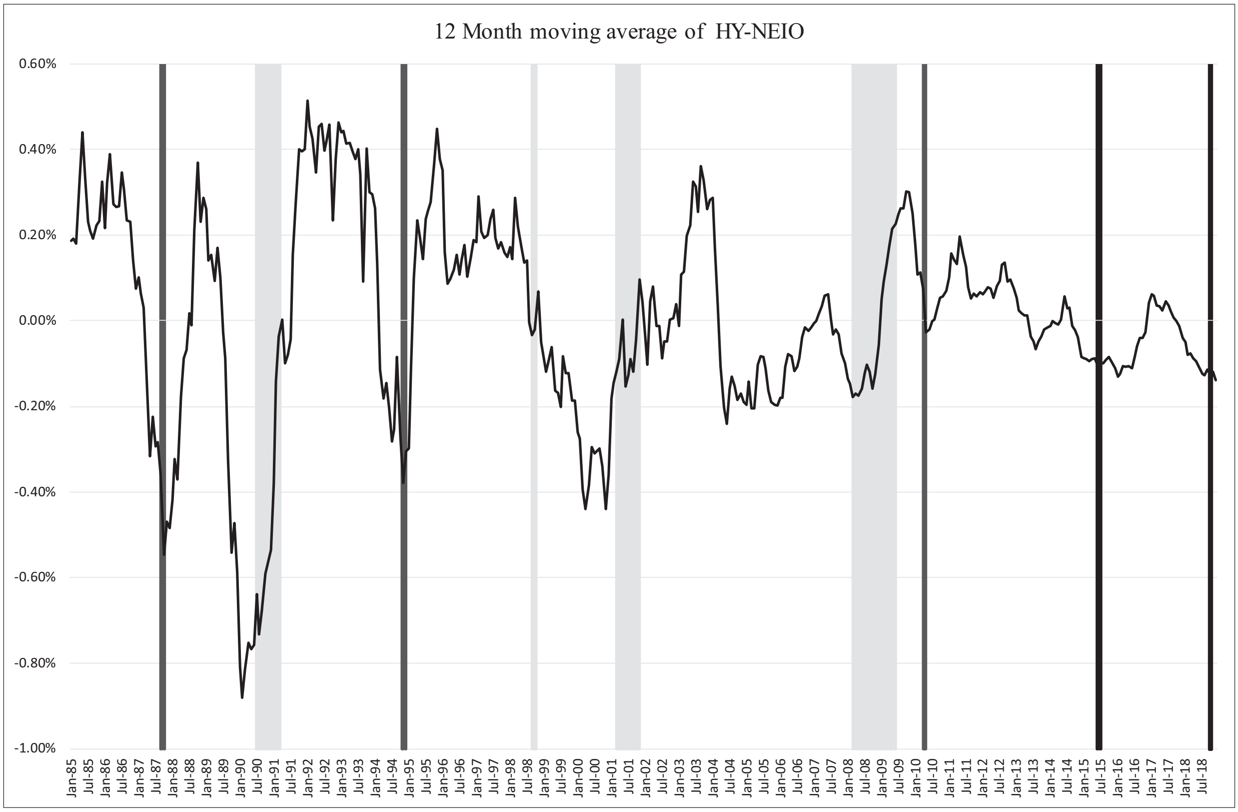


Fig. 1. 12-month moving averages of HY-NEIO. In this figure we plot the 12-month moving averages of HY-NEIO from January 1985 (i.e., February 84–January 85) through December 2018. HY-NEIO is net exchanges (exchanges-in minus exchanges-out) from high-yield corporate bond funds normalized by the end-of-previous-month assets. The data are obtained from the ICI and run from February 1984 through December 2018. The three light gray columns represent NBER recession periods. The dark gray columns represent the 1987 market crash, the Mexican Peso crisis in 1994, the European sovereign debt crisis in early 2010, the high-yield spread hike during June 2015–February 2016, and the market crash in the last quarter of 2018.

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 et al. (2017), we use the log of HYS in regression analyses.

Table 2 presents the regression results showing that HY-NEIO positively predicts the future HYS.[10] In Columns 1 and 2, we regress quarterly log HYS on average HY-NEIO over the past four quarters. The coefficient estimates on HY-NEIO are positive and statistically significant at the 1% levels. The economic magnitude of the coefficient estimates on HY-NEIO is also substantial. For example, a one-standard-deviation increase in HY-NEIO in Column 2 is associated with a 2.72% increase in HYS.

Greenwood and Hanson (2013) and Lopez-Salido et al. (2017) measure HYS over four quarters. Given the importance of HYS in predicting credit and business cycles, in Columns 3 and 4 of Table 2 we examine the predictive relation between lagged HY-NEIO and HYS measured over the same horizon. We find that the results are both statistically and economically significant. In addition, the univariate correlation between HYS and lagged HY-NEIO is 0.49. The fact that HY-NEIO is able to predict HYS over the horizon used in these papers further reveals the importance of HY-NEIO in connection with credit and business cycles.

In Fig. 2, we also examine the dynamic relationship between HY-NEIO and the HYS using impulse response functions based on a quarterly VAR (vector autoregression) with four lags of each variable. The response of the HYS to a one-standard-deviation shock in HY-NEIO is positive and significant, consistent with the results of our predictive regressions shown in Table 2. This is consistent with HY-NEIO's moving first, capturing future demand in credit markets and more high-yield bond issuance (Erel et al., 2012). In contrast, the response of HY-NEIO to a one-standard-deviation shock in HYS is negative and significant, suggesting that HY-NEIO is trending down after an increase in HYS.

3.2. Predicting reaching for yield

We further examine whether HY-NEIO can predict the relative amounts of higher-yielding corporate bonds in

[10] In Table 2 we show the results of regressing levels of HYS and RFY. Using first differences of HYS and RFY yields qualitatively similar results.

Table 2
Regressions of future high-yield share and reaching for yield on HY-NEIO.
In this table we present the results of quarterly predictive time-series regressions of future high-yield share (HYS) and reaching for yield (RFY) on HY-NEIO and other explanatory variables. HYS (Columns 1–4) is the log of the high-yield share, which is defined as the dollar fraction of nonfinancial high-yield-rated debt issues. RFY (Columns 5–8) 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 RFY measure, RFY_t. We regress the dependent variables, HYS and RFY, measured over quarter $q+1$ and 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-month T-bill rate (TB); and the dividend yield (DY), calculated as the sum of all dividends for the previous 12 months divided by total market capitalization. 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 the total corporate bond spread and the spread component that is predicted by expected defaults. The sample period ranges from February 1984 to December 2018. The EBP data end in September 2016. Standard errors are calculated using Newey-West (1987) correction, where the number of lags is based on the quarterly overlapping period. t-statistics (in parentheses) are reported below the coefficient estimates.

	HYS				RFY			
	$q+1$		$q+1{:}q+4$		$q+1$		$q+1{:}q+4$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO *q-3:q*	0.065	0.077	0.087	0.112	0.008	0.006	0.018	0.017
	(3.43)	(3.75)	(4.15)	(4.70)	(3.08)	(2.15)	(4.53)	(3.73)
DEP *q-3:q*	0.433	0.290	0.224	0.149	0.169	0.089	0.041	0.031
	(3.11)	(2.18)	(2.21)	(1.46)	(2.53)	(2.00)	(0.42)	(0.28)
TS *q*	−3.438	−16.881	−1.583	−2.977	−1.232	−0.867	−4.151	−3.915
	(−0.37)	(−2.34)	(−0.21)	(−0.37)	(−1.14)	(−0.66)	(−2.66)	(−2.20)
DS *q*	−23.805	−25.923	−15.533	−5.589	−2.329	−4.303	−10.590	−14.027
	(−1.20)	(−1.40)	(−1.09)	(−0.30)	(−1.16)	(−1.26)	(−2.47)	(−2.58)
TB *q*	−7.137	−14.402	−12.142	−14.855	−0.592	−0.452	−2.676	−2.706
	(−1.48)	(−3.86)	(−3.03)	(−3.69)	(−1.22)	(−0.85)	(−2.25)	(−2.27)
DY *q*	0.489	11.868	−0.170	3.602	3.706	4.931	15.843	16.670
	(0.04)	(1.34)	(−0.01)	(0.28)	(2.08)	(2.21)	(2.74)	(2.64)
HYS *q-3:q*						0.033		0.021
						(1.30)		(0.86)
EBP *q*		−0.275		−0.352		0.022		0.033
		(−1.79)		(−2.07)		(0.72)		(1.28)
HYRET *q-3:q*		−0.003		−0.013		0.000		0.001
		(−0.56)		(−1.77)		(0.34)		(0.84)
Adj R^2	0.359	0.520	0.598	0.685	0.157	0.172	0.548	0.551

each rating category, which we interpret as a degree of RFY in the corporate bond market. As Rajan (2013) and Stein (2013) note, an ultra-low interest rate environment can lead to credit-market booms and excessive risk-taking on the part of investors. For example, mutual funds tend to hold higher-yield securities in a given rating category when the credit market is booming, as their investment mandate is typically based on credit ratings (Choi and Kronlund, 2018).

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 in the credit market. Finally, our RFY measure is defined as the average of RFY_{jt} across all rating categories.[11]

In Table 2, in Columns 5 through 8, we present the regression results of RFY on lagged HY-NEIO. We find that HY-NEIO strongly predicts future RFY, as the coefficient estimates on HY-NEIO are all positive and highly statistically significant. We find that the coefficient estimates are also economically significant, as a one-standard-deviation increase in HY-NEIO is associated with an increase of 1.7% in RFY over the next quarter, and an increase of 5.3% in RFY over the next four quarters. 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 of credit cycles, while the EBP does not help predict future RFY as shown by insignificant, positive coefficients.

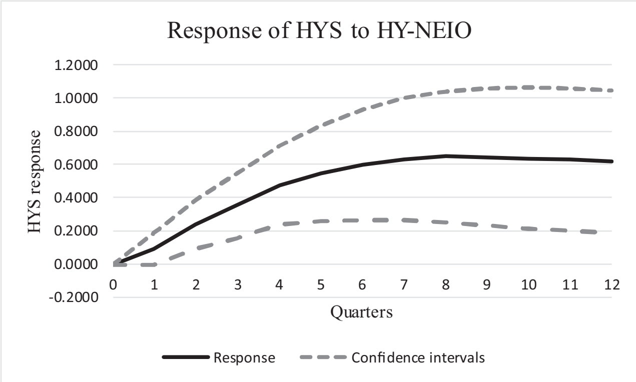
In summary, the results provided in Table 2 show that HY-NEIO consistently predicts indicators associated with credit cycles. That is, investor flow shifts into HY bond funds signals that future credit market conditions will improve.

3.3. Predicting credit spreads and the excess bond premium

Recent studies have found that credit spreads are important indicators of business cycle variation. For example, Gilchrist and Zakrajšek (2012) argue that credit spreads represent not only the default risk of corporate issuers

[11] In the Internet Appendix, we also report results using a value-weighted average of RFY across rating categories and find qualitatively similar results.

(a) Cumulative impulse response of HYS to a 1 SD shock in HY-NEIO



(b) Cumulative impulse response of HY-NEIO to a 1 SD shock in HYS

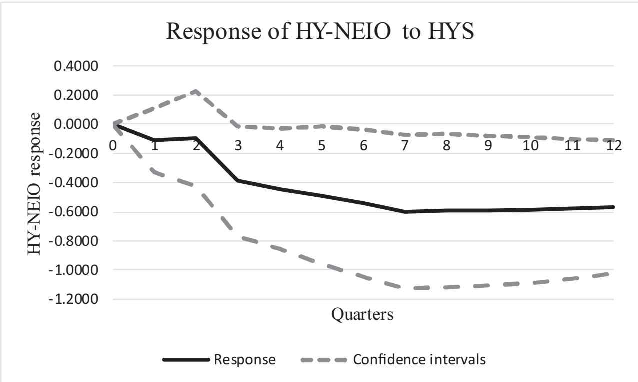


Fig. 2. Impulse response of HYS and HY-NEIO. In this figure we plot the impulse responses of quarterly log of the high-yield share (HYS) and HY-NEIO to a one-standard-deviation (1 SD) shock in HY-NEIO and the HYS, respectively. We estimate a quarterly VAR (vector autoregression) system of HYS and HY-NEIO with four lags of each of the dependent variables. We include the lagged default spread (DS), lagged term spread (TS), lagged 3-month T-bill rate (TB), and lagged EBP as additional control variables. The VAR includes 126 quarterly observations. In graphs (a) and (b) we 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 year 0 (marked as 0 on the *x*-axis) and run 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).

but also deterioration in the capital position of financial intermediaries and the resulting reduction in the supply of credit. Krishnamurthy and Muir (2015) show that credit spreads are an important variable for predicting 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) show that the high-yield spread (i.e., the difference between the average spread of junk-rated bonds and Aaa bonds) has significant predictive power for future business cycles.

Given that HY-NEIO is an early indicator of 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 Gilchrist and Zakrajšek's EBP spread, which is the difference between total corporate bond spreads and the spread component that is predicted by expected defaults from the Black-Scholes-Merton model of credit risk.

In Table 3, Panel A, we report the results of predictive regressions of the future high-yield and default spreads on HY-NEIO in Columns 1 through 4 and 5 through 8, respectively. In particular, we regress quarter 1 $(q+1)$ and quarter 4 $(q+4)$ future spreads on current HY-NEIO and other control variables. Our results show that HY-NEIO negatively predicts both the high-yield and default spreads over the next one to four quarters, across all the specifications considered. In Columns 1 through 4, for example, the coefficient estimates on HY-NEIO are all negative and statistically significant at the 1% level. Moreover, the coefficient estimates are more negative in quarter 4. The economic magnitude of the coefficients is sizable, as a one-standard-deviation decrease in HY-NEIO translates into 0.34%–0.77% increases in the high-yield spread. In Columns 5 through 8, we also find that HY-NEIO negatively predicts the future default spread, as shown by the coefficient estimates on lagged HY-NEIO that are negative and statistically significant at the conventional

Table 3
Regression of future credit spreads and the future EBP on HY-NEIO.

In this table we present 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 quarter ($q+1$) and 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 ranges from February 1984 to December 2018. EBP data end in September 2016. Standard errors are calculated using the Newey-West correction, where the number of lags is based on the quarterly overlapping period. t-statistics (in parentheses) are reported below the coefficient estimates.

Panel A: HY-Aaa and Baa-Aaa credit spreads on HY-NEIO

	HY-Aaa				Baa-Aaa			
	$q+1$		$q+4$		$q+1$		$q+4$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO *q-3:q*	−0.1174	−0.1578	−0.1873	−0.2655	−0.0148	−0.0167	−0.0193	−0.0285
	(−3.00)	(−3.26)	(−3.05)	(−3.29)	(−2.64)	(−2.16)	(−1.79)	(−2.41)
Spread *q*	0.792	0.653	0.242	−0.090	0.814	0.684	0.366	0.224
	(5.86)	(4.10)	(2.75)	(−0.52)	(5.98)	(4.64)	(2.29)	(1.36)
TS *q*	13.954	17.601	−14.537	−14.210	2.778	2.957	0.113	0.301
	(1.38)	(1.37)	(−0.50)	(−0.44)	(1.45)	(1.19)	(0.03)	(0.06)
TB *q*	11.684	16.226	26.076	31.259	0.807	0.692	1.364	1.687
	(2.41)	(3.11)	(2.84)	(2.79)	(1.05)	(−0.65)	(0.61)	(0.60)
DY *q*	−19.653	−14.843	−23.644	−11.709	−1.930	0.928	−6.098	−2.899
	(−1.30)	(−0.91)	(−0.58)	(−0.28)	(−0.70)	(0.35)	(−0.83)	(−0.41)
HYS *q-3:q*		0.326		0.420		0.065		0.102
		(1.37)		(1.03)		(1.52)		(1.12)
EBP *q*		0.924		1.880		0.153		0.215
		(1.75)		(2.30)		(1.71)		(2.11)
HYRET *q-3:q*		0.007		0.012		0.001		0.005
		(0.55)		(0.72)		(0.51)		(1.49)
Adj R^2	0.736	0.741	0.295	0.344	0.652	0.655	0.096	0.106

Panel B: EBP on HY-NEIO

	AveEBP $q+1$		
	(1)	(2)	(3)
HY-NEIO *q*	−0.0529	−0.0519	−0.0524
	(−2.65)	(−2.54)	(−2.57)
AveEBP *q*	0.8285	0.8445	0.8222
	(9.64)	(10.04)	(8.98)
TS *q*		2.611	2.067
		(0.77)	(0.64)
TB *q*		2.475	2.014
		(1.63)	(1.47)
DY *q*		−5.490	−5.822
		(−1.16)	(−1.20)
HYS *q-3:q*			−0.042
			(−1.00)
Adj R^2	0.696	0.695	0.694

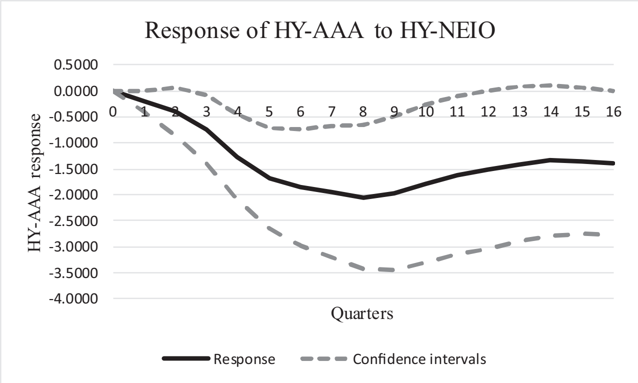
levels. Summarizing the results, a heavier allocation of investor money into high-yield funds predicts lower credit spreads (i.e., higher corporate bond prices) in the next year.

Fig. 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 shown in Panel A of Table 3. A negative one-standard-deviation shock to HY-NEIO is associated with an increase in the high-yield spread, which lasts around eight quarters. Interestingly, there are signs of reversal in credit spreads from quarter 9, which suggests that credit cycles revert to the mean at some point.

In Panel B of Table 3 we provide results from regressions of quarterly averages 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.

Fig. 4 plots the impulse response functions of HY-NEIO and the EBP estimated from a quarterly VAR with one lag. A comparison of Fig. 4(a) and (b) shows that HY-NEIO has a significant effect on the future EBP but not vice versa.

(a) Cumulative impulse response of HY-Aaa to a 1 SD shock in HY-NEIO



(b) Cumulative impulse response of HY-NEIO to a 1 SD shock in HY-Aaa

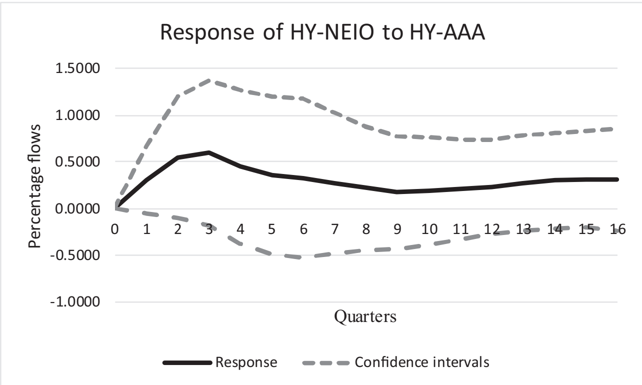


Fig. 3. Impulse response of HY spread and HY-NEIO. In this figure we plot the impulse responses of the quarterly HY-Aaa spread and HY-NEIO to a one-standard-deviation (1 SD) shock in HY-NEIO and HY-Aaa, respectively. We estimate a quarterly VAR (vector autoregression) system of HY-Aaa and HY-NEIO with eight lags of each of the dependent variables. We include the lagged default spread (DS), lagged term spread (TS), lagged 3-month T-bill rate (TB), and lagged EBP as additional control variables. The VAR includes 122 quarterly observations. In graphs (a) and (b) we 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) and run 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).

A one-standard-deviation shock to HY-NEIO translates to a decrease in the EBP of 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 0.55. In comparison, the impulse responses of HY-NEIO given EBP shocks are not statistically significant.

3.4. Predicting growth in financial intermediary balance sheets and aggregate bond issuance

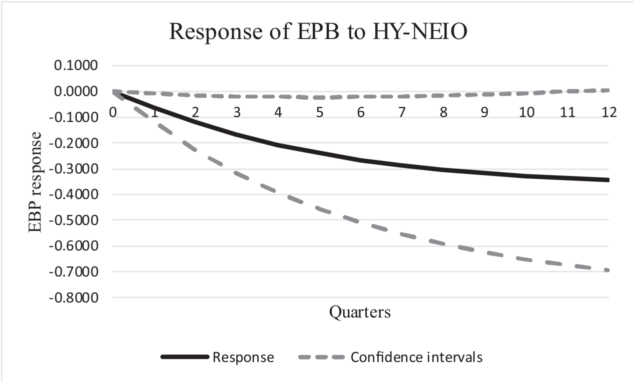
A growing body of literature shows the importance of the role played by changes in the balance sheets of financial intermediaries in both the financial markets and real economy. Schularick and Taylor (2012) and Krishnamurthy and Muir (2015), for example, show that the severity of financial crises and recessions is closely related to increases in intermediary balance sheets and credit supply prior to crises. In this section, we examine whether HY-NEIO positively predicts growth in financial intermediary balance sheets measured as quarterly differences in the financial sector's assets divided by the previous quarter's assets.[12] In addition, 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 businesses.[13]

In Table 4 we report the predictive regression results. In Columns 1 through 3, we regress quarterly growths in intermediary balance sheets on HY-NEIO and other explanatory variables. The results indicate that HY-NEIO positively predicts balance sheet growth in the next quarter. For example, the coefficient estimates on HY-NEIO are all positive and statistically significant at the 5% level. A

[12] The data are obtained from Table L.129 of the Federal Reserve Flow of Funds (see also Adrian et al., 2014).

[13] 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.

(a) Cumulative impulse response of EBP to a 1 SD shock in HY-NEIO



(b) Cumulative impulse response of HY-NEIO to a 1 SD shock in EBP

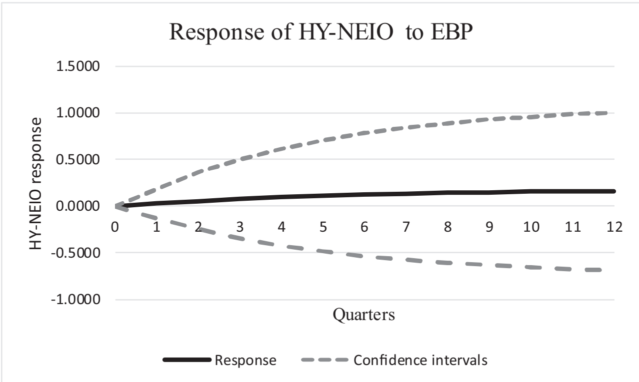


Fig. 4. Impulse response of excess bond premium and HY-NEIO. In this figure we plot the impulse response of the quarterly excess bond premium and HY-NEIO to a one-standard-deviation (1 SD) shock in HY-NEIO and the EBP, respectively. The excess bond premium (EBP) is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. We estimate the quarterly VAR (vector autoregression) system of the EBP and HY-NEIO with one lag of each of the dependent variables. We include the lagged default spread (DS), lagged term spread (TS), and the lagged 3-month T-bill rate (TB) as additional control variables. The VAR includes 129 quarterly observations. In graphs (a) and (b) we plot the cumulative response of the EBP to a one-standard-deviation shock in HY-NEIO and HY-NEIO to a one-standard-deviation shock in the EBP, respectively. The graphs start at quarter 0 (marked as 0 on the *x*-axis) and run 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).

one-standard-deviation increase in HY-NEIO translates into 0.92%–1.00% 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 investor portfolio shifts into high-yield bonds and growth in assets of the financial sector.

In Columns 4 through 6, we present the results of regressing 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 of around 0.30% in the next quarter. These results are also robust to controlling for bond index returns, which covers the possibility that market timing in bond markets (e.g., Baker and Wurgler, 2002) simultaneously drives both NBI and HY-NEIO. Note that the predictability of the HYS reported in Table 2 is much stronger than the predictability of NBI. This result is consistent with results reported by Erel et al. (2012), who show that for non-investment-grade borrowers, capital raising tends to be procyclical, while for investment-grade borrowers it is countercyclical. Overall, the results shown in Table 4 suggest that HY-NEIO is able to predict growth in the financial sector's balance sheet and net bond issuance.

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 fund flows that leads aggregate investor demand, the results we have reported so far show that HY-NEIO predicts leading business cycle indicators suggested in the literature. We ask an important follow-up question: can HY-NEIO predict economic fluctuations *earlier* than leading indicators in the literature, e.g., credit spreads, the EBP, or the HYS? In this section, we provide strong empirical evidence showing that HY-NEIO is an early indicator for future GDP and

Table 4
Regressions of future growth in intermediary balance sheets and net bond issuance on HY-NEIO.
In this table we present the results of quarterly predictive time-series regressions of growth in intermediary balance sheet assets (dA/A) and net bond issuance (NBI) on HY-NEIO and other explanatory variables. dA/A is the difference in balance sheet assets between end of the quarter and end of the previous quarter divided by 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 et al. (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 the 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 the high-yield bond index for the past year (HYRET). The sample period ranges from February 1984 to December 2018. EBP data end in September 2016. 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 in parentheses below the coefficient estimates.

	dA/A $q+1$			NBI $q+1$		
	(1)	(2)	(3)	(4)	(5)	(6)
HY-NEIO q-3:q	0.0035	0.0032	0.0034	0.0008	0.0008	0.0010
	(2.42)	(2.21)	(2.33)	(2.12)	(2.10)	(2.13)
DEP q-3:q	−0.004	0.001	0.003	0.654	0.672	0.679
	(−0.13)	(0.01)	(0.09)	(5.21)	(4.86)	(5.12)
TS q	1.161	1.019	1.038	−0.117	−0.186	−0.169
	(2.05)	(1.49)	(1.46)	(−0.96)	(−1.33)	(−1.14)
DS q	−1.436	2.150	2.142	0.589	0.516	0.503
	(−0.96)	(1.50)	(1.49)	(2.08)	(1.12)	(1.08)
TB q	0.968	0.994	0.978	0.074	0.035	0.029
	(2.66)	(2.84)	(2.83)	(1.37)	(0.46)	(0.37)
DY q	−0.265	−0.982	−0.968	0.039	0.085	0.091
	(−0.35)	(−1.23)	(−1.20)	(0.19)	(0.39)	(0.41)
HYS q-3:q		−0.016	−0.016		−0.001	−0.001
		(−1.45)	(−1.53)		(−0.39)	(−0.47)
EBP q		−0.037	−0.038		0.000	−0.001
		(−2.46)	(−2.53)		(−0.10)	(−0.41)
HYRET q-3:q			0.000			0.000
			(−0.28)			(−0.84)
Adj R^2	0.158	0.195	0.189	0.450	0.441	0.440

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

In Table 5, Panel A, we present results from regressions of future changes in real GDP growth on HY-NEIO and other control variables, including the HYS and EBP. We find that the predictive ability of HY-NEIO tends to become stronger in the more distant future, consistent with our idea that it is an early economic indicator. In Columns 1 and 2, for example, we do not find strong statistical support that HY-NEIO predicts real GDP growth in the next quarter. In contrast, in Columns 3 through 4 we regress GDP growth in quarter $q+4$ (i.e., from three quarters after to four quarters after), and show that the coefficient estimates on HY-NEIO are positive and highly statistically significant, indicating that HY-NEIO signals changes in GDP multiple quarters in advance.

To examine the longer-run predictability of HY-NEIO and further contrast HY-NEIO with EBP and HYS, we regress changes in real GDP growth over the next four (eight) quarters on HY-NEIO and report the results in Columns 5 and 6 (Columns 7 and 8). 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 longer horizons. The coefficient estimates are economically significant as well, as a one-standard-deviation increase in HY-NEIO translates into a 0.64%–0.88% increase in GDP. In contrast, we do not find statistically significant coefficient estimates on either the EBP or the HYS after four quarters, showing that the predictive power of these variables is concentrated largely in the shorter horizons.

The results provided in Panel A suggest that HY-NEIO serves as an early business cycle indicator by predicting changes in 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 components of 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 the EBP, as shown in Fig. 5(a) and (b), respectively, using the VAR. A comparison of the two figures shows that HY-NEIO is an early indicator, compared with the EBP. A one-standard-deviation shock to HY-NEIO leads to a statistically significant change in GDP growth only after four quarters, as can be seen from the confidence intervals of the impulse response. In contrast, Fig. 5(b) indicates that a one-standard-deviation shock to the EBP affects GDP immediately starting one quarter after the shock. In the Internet Appendix, we also verify that differences in the impulse responses to HY-NEIO and EBP shocks are statistically significant at the 5% level, using Monte-Carlo simulations to calculate their confidence intervals. In particular, the results reported in Table IA.2 show that the difference between HY-NEIO and EBP impulse response functions for quarters 1 and 2 is −0.0035 with a p-value of 0.028,

Table 5
Regressions of future changes in real GDP and unemployment rate on HY-NEIO.

In this table we present the results of quarterly predictive regressions of changes in real GDP growth and changes in the unemployment rate on HY-NEIO. In Panel A, the dependent variables are changes in log real GDP (GDP) over the next first quarter (Columns 1–2), the next fourth quarter (Columns 3–4), the next four quarters (Columns 5–6), and over the next eight quarters (Columns 7–8). The explanatory variables are HY-NEIO, changes 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 variables are changes in the unemployment rate (UR). Similar to Panel A, UR is measured over the next first quarter (Columns 1–2), the next fourth quarter (Columns 3–4), the next four quarters (Columns 5–6), and over the next eight quarters (Columns 7–8). The explanatory variables are the same as those used in Panel A. In the row marked by 1 SD HY-NEIO we show the one-standard-deviation effect of HY-NEIO on GDP and UR. The sample period ranges from February 1984 to December 2018. EBP data end in September 2016. 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 in parentheses below the coefficient estimates.

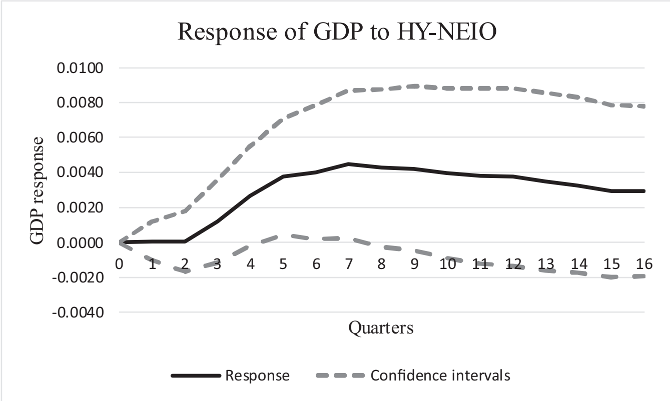
Panel A: Changes in real GDP on HY-NEIO

	GDP							
	$q+1$		$q+4$		$q+1{:}q+4$		$q+1{:}q+8$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO *q-3:q*	0.0005	0.0002	0.0005	0.0008	0.0022	0.0024	0.0025	0.0030
	(2.57)	(1.27)	(3.01)	(3.88)	(3.25)	(3.02)	(2.26)	(2.38)
GDP *q-3:q*	0.070	0.006	0.038	0.039	0.195	0.101	0.337	0.214
	(1.97)	(0.15)	(1.21)	(0.94)	(1.62)	(0.63)	(1.60)	(0.71)
TS *q*	0.069	0.140	0.106	0.149	0.314	0.483	1.152	1.423
	(1.38)	(2.24)	(1.86)	(2.17)	(1.85)	(2.46)	(2.42)	(3.25)
DS *q*	−0.422	−0.136	−0.035	0.142	−0.859	−0.035	−0.481	−0.141
	(−2.94)	(−0.79)	(−0.19)	(0.73)	(−1.82)	(−0.06)	(−0.72)	(−0.15)
TB *q*	0.027	0.099	0.031	0.037	0.121	0.236	0.340	0.478
	(1.12)	(2.96)	(1.26)	(0.91)	(1.69)	(1.77)	(2.31)	(2.03)
DY *q*	−0.019	−0.086	−0.030	−0.084	−0.093	−0.298	−0.488	−0.608
	(−0.23)	(−0.98)	(−0.32)	(−0.84)	(−0.29)	(−1.14)	(−0.82)	(−1.00)
HYS *q-3:q*		0.002		−0.001		0.001		0.003
		(1.59)		(−0.89)		(0.12)		(0.46)
EBP *q*		−0.002		−0.003		−0.010		−0.007
		(−1.64)		(−2.04)		(−2.14)		(−0.89)
HYRET *q-3:q*		0.000		0.000		0.000		0.000
		(0.63)		(−2.97)		(−1.72)		(−1.93)
1 SD HY-NEIO	0.13%	0.07%	0.15%	0.22%	0.64%	0.68%	0.73%	0.88%
Adj R^2	0.232	0.283	0.086	0.119	0.326	0.363	0.306	0.316

Panel B: Changes in unemployment rate on HY-NEIO

	UR							
	$q+1$		$q+4$		$q+1{:}q+4$		$q+1{:}q+8$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HY-NEIO *q-3:q*	−0.0168	−0.0011	−0.0362	−0.0314	−0.117	−0.083	−0.188	−0.137
	(−2.07)	(−0.10)	(−4.77)	(−3.52)	(−4.27)	(−3.40)	(−3.82)	(−2.99)
UR *q-3:q*	0.113	0.081	0.094	0.079	0.418	0.326	0.569	0.524
	(4.06)	(2.76)	(2.89)	(1.78)	(2.74)	(2.02)	(3.26)	(2.44)
TS *q*	−2.878	−2.724	−4.408	−3.879	−12.293	−11.401	−45.364	−46.587
	(−1.11)	(−0.90)	(−1.65)	(−1.27)	(−1.58)	(−1.17)	(−2.01)	(−1.90)
DS *q*	31.887	17.250	3.240	−6.801	67.427	13.765	59.410	11.943
	(3.05)	(1.60)	(0.49)	(−0.80)	(2.06)	(0.56)	(1.29)	(0.30)
TB *q*	2.258	0.816	2.555	2.233	10.007	6.740	19.861	14.491
	(2.05)	(0.56)	(2.26)	(1.59)	(2.20)	(1.40)	(2.49)	(1.50)
DY *q*	−5.602	−4.985	−5.857	−5.025	−24.118	−20.122	−44.097	−36.144
	(−1.33)	(−1.02)	(−1.40)	(−1.07)	(−1.54)	(−1.31)	(−1.58)	(−1.47)
HYS *q-3:q*		−0.059		0.006		−0.060		−0.113
		(−1.20)		(0.09)		(−0.28)		(−0.31)
EBP *q*		0.119		0.112		0.554		0.236
		(2.10)		(1.37)		(2.29)		(0.60)
HYRET *q-3:q*		−0.004		−0.001		−0.007		−0.018
		(−1.48)		(−0.36)		(−0.90)		(−1.43)
1 SD HY-NEIO	−0.05%	0.00%	−0.10%	−0.09%	−0.34%	−0.24%	−0.54%	−0.39%
Adj R^2	0.383	0.443	0.274	0.282	0.484	0.549	0.502	0.510

(a) Cumulative response to HY-NEIO



(b) Cumulative response to EBP

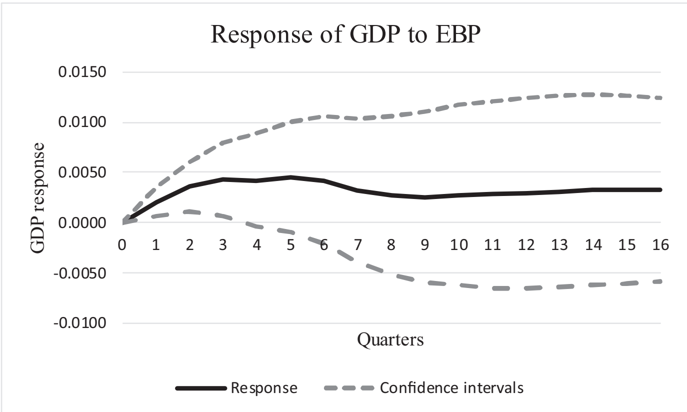


Fig. 5. Impulse response of real GDP changes to HY-NEIO and EBP. In this figure we plot the impulse responses of quarterly changes in real GDP growth (GDP) to a one-standard-deviation (1 SD) shock in HY-NEIO and the EBP, where the EBP is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. For comparison between HY-NEIO and the EBP responses, the EBP shock is multiplied by −1. We estimate the quarterly VAR (vector autoregression) system of GDP, HY-NEIO, and the EBP with eight lags of each of the dependent variables. We include the lagged default spread (DS), lagged term spread (TS), and lagged 3-month T-bill rate (TB) as additional control variables. The VAR includes 122 quarterly observations. In graphs (a) and (b), we plot the cumulative response of GDP to a one-standard-deviation shock in HY-NEIO and the EBP, respectively. The graphs start at quarter 0 (marked as 0 on the *x*-axis) and run 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).

thus showing that the response of GDP to the EBP is more immediate.

In Panel B of Table 5, we report the results of examining the predictability of unemployment rate changes, as in our analyses presented in Panel A. Our conclusions inferred from these results are largely the same as those inferred from the results based on GDP growth. In particular, the coefficient estimates on HY-NEIO are highly statistically significant four quarters after (Columns 3 and 4), in the next four quarters (Columns 5 and 6), and also in the next eight quarters (Columns 7 and 8). In comparison, the coefficient estimates on the EBP are significant at the 5% level only during quarters 1 through 4 (Columns 5 and 6) but not during quarters 1 through 8 (Columns 7 and 8) and the coefficient estimates on the HYS are not statistically significant in any of the columns.

Like the impulse response results plotted in Fig. 5 for GDP growth, Fig. 6 shows that HY-NEIO is an early predictor of future unemployment rate changes, compared with the EBP. As in Fig. 5, the impulse responses indicate that a shock in HY-NEIO leads to a negative peak only after eight quarters, while a shock to the EBP appears immediately. The Wald test results provided in the Internet Appendix also confirm that the EBP moves first in quarters 1 and 2 (a p-value of 0.003). Overall, these results confirm that HY-NEIO is an early indicator of future economic activities, i.e., real GDP growth and unemployment rate changes.

Fig. 7 depicts the timeline of HY-NEIO, the HYS, and credit spreads in the order of their predictive 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

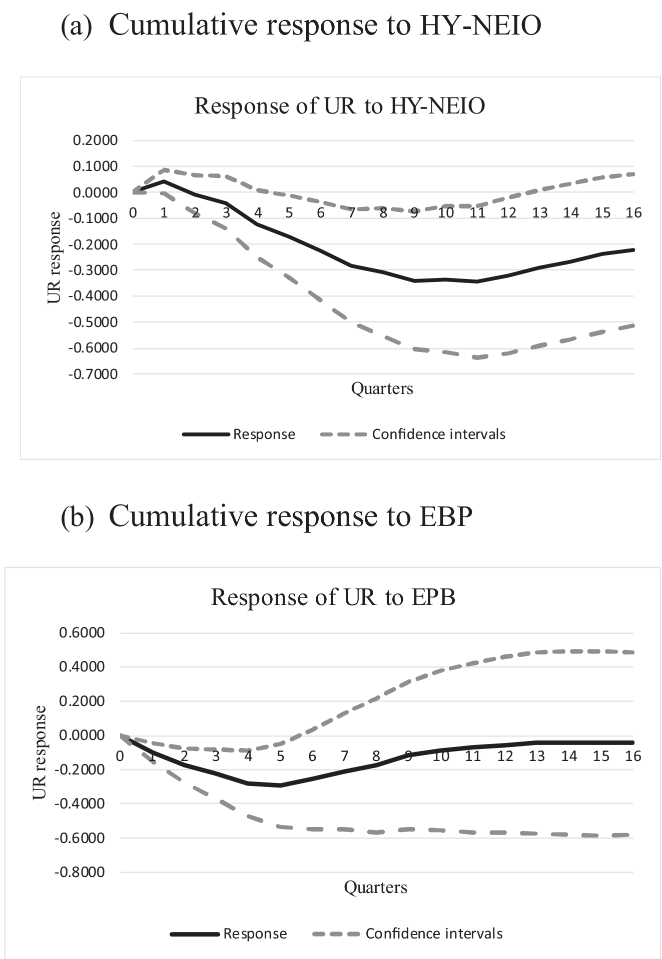


Fig. 6. Impulse response of unemployment changes to HY-NEIO and EBP. In this figure we plot the impulse responses of quarterly changes in unemployment rates (UR) to a one-standard-deviation shock in HY-NEIO and the EBP, where the EBP is Gilchrist and Zakrajšek's (2012) excess bond premium averaged over the quarter. For comparison between HY-NEIO and EBP responses, the EBP one-standard-deviation shock is multiplied by −1. EBP data end in September 2016. We estimate the quarterly VAR (vector autoregression) system of UR, HY-NEIO, and the excess bond premium with four lags. We include the lagged default spread (DS), lagged term spread (TS), and lagged 3-month T-bill rate (TB) as additional control variables. The VAR includes 122 quarterly observations. In graphs (a) and (b) we plot the cumulative response of UR to a one-standard-deviation shock in HY-NEIO and the EBP, respectively. The graphs start at quarter 0 (marked as 0 on the *x*-axis) and run 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).

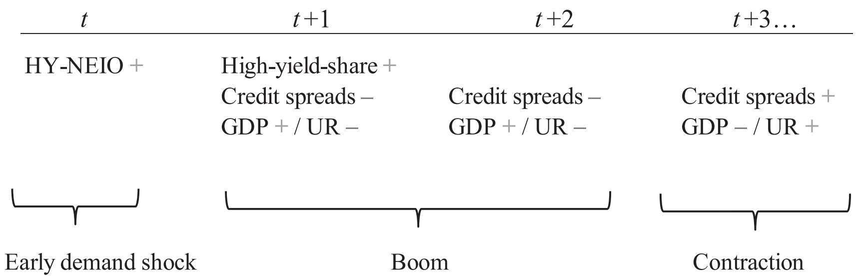


Fig. 7. Timeline of dynamics in economic and credit cycle indicators. This figure shows the timeline for the dynamics of HY-NEIO, the high-yield share (HYS), credit spreads, GDP growth, and unemployment rate (UR) changes. For the sake of brevity, we show only the dynamics of a positive shock in HY-NEIO. The same dynamics should apply for a negative shock in HY-NEIO, followed by contraction and subsequent expansion.

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 reached after 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), lagged changes in log real GDP (GDP), and lagged changes in the unemployment rate (UR). The sample period ranges from February 1984 to December 2018. EBP data end in September 2016. 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 in parentheses 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	0.203	0.186	0.169	0.208	0.142	0.121	0.250	0.217	0.071	0.054	0.133	0.118
	(3.34)	(2.67)	(2.59)	(2.24)	(2.14)	(1.87)	(3.80)	(2.52)	(2.08)	(1.75)	(3.15)	(2.37)
DEP q-3:q	0.569	0.276	−0.360	−0.286	0.572	0.177	−0.384	−0.472	0.083	−0.296	0.155	0.388
	(2.80)	(1.25)	(−1.74)	(−1.20)	(2.40)	(0.94)	(−2.02)	(−1.93)	(0.42)	(−1.68)	(0.76)	(1.63)
TS q	95.259	101.180	82.516	96.843	116.740	121.544	68.723	78.947	−18.597	−9.818	7.916	18.054
	(2.11)	(2.68)	(2.51)	(2.41)	(2.52)	(3.19)	(2.17)	(2.77)	(−0.71)	(−0.43)	(0.26)	(0.60)
DS q	−13.906	−25.301	−81.044	−73.636	−3.095	76.386	−71.853	−50.722	−202.176	−152.625	−5.607	−61.602
	(−0.23)	(−0.33)	(−1.14)	(−0.83)	(−0.05)	(0.80)	(−1.10)	(−0.62)	(−2.48)	(−2.37)	(−0.08)	(−0.82)
TB q	−20.809	−21.826	−17.934	−14.241	−15.029	−7.842	−17.099	−7.341	−61.473	−47.705	−40.498	−37.540
	(−1.52)	(−1.54)	(−1.31)	(−0.92)	(−1.05)	(−0.43)	(−1.21)	(−0.41)	(−3.69)	(−3.31)	(−2.19)	(−1.95)
DY q	10.489	67.447	6.067	−25.300	−6.489	22.322	4.976	−18.194	203.068	217.953	139.364	126.454
	(0.21)	(2.13)	(0.11)	(−0.46)	(−0.12)	(0.56)	(0.10)	(−0.35)	(4.69)	(6.00)	(2.65)	(2.56)
HYS q-3:q		1.414		−0.331		1.239		0.204		0.708		0.007
		(3.33)		(−0.67)		(3.09)		(0.37)		(2.60)		(0.02)
EBP q		0.007		0.936		−0.473		1.025		−0.523		0.680
		(0.01)		(1.53)		(−1.05)		(1.60)		(−1.73)		(1.62)
HYRET q-3:q		−0.036		0.011		−0.027		0.031		−0.014		0.024
		(−2.27)		(0.50)		(−1.29)		(1.07)		(−1.09)		(0.86)
GDP q-3:q		40.469		−6.898		28.619		−7.394		−21.223		−5.446
		(1.74)		(−0.29)		(1.21)		(−0.29)		(−2.00)		(−0.33)
UR q-3:q		0.348		−0.650		−0.135		−0.722		−0.510		0.280
		(0.86)		(−2.51)		(−0.25)		(−2.24)		(−2.69)		(1.15)
Adj R^2	0.450	0.590	0.545	0.576	0.398	0.553	0.546	0.584	0.697	0.812	0.653	0.724

$t+1$. It also predicts GDP and unemployment rates on a longer horizon, up to year $t+2$. In comparison, as Lopez-Salido et al. (2017) show, an increase in the 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 summary, HY-NEIO moves a year in advance before the existing credit and business cycle indicators.

4.2. Predicting future monetary policy

In Table 6 we examine 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) (R&R, henceforth), the latter of which captures unexpected shocks caused by Fed policies.[14] Given the persistent nature of changes in monetary policy, we focus on two-year-horizon policy changes, where we regress future 24-month changes in the discount rate, the federal funds rate, and the R&R measure on HY-NEIO.[15]

Table 6 presents the regression results. The results reported in 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 predictive 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 find similar results in Columns 5 and 6 and Columns 9 and 10 based on the federal funds rate and R&R, respectively, showing that an increase in HY-NEIO forecasts tighter monetary policies for the next eight 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-month changes in monetary policy on explanatory variables by skipping the first 12 months, as

[14] 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/.

[15] As the data are reported at quarterly frequency, we employ overlapping observations for the dependent variable. To circumvent the statistical issue associated with using overlapping observation, we also examine quarterly changes in monetary policies. In untabulated results, we obtain rather consistent results, although they are somewhat weaker.

Table 7
Out-of-sample performance.
In this table we present the results of root-mean-squared forecasting errors (RMSE) of one-year- or two-years-ahead changes in real GDP growth (GDP) and changes in the unemployment rate (UR), using regression coefficients from 10-year rolling estimation windows. In each quarter q, we first estimate regression coefficients using the 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. In Panel A we report 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. In Panel B we report 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. In the last four columns (Statistics) we report the average (Avg.) and standard deviation (Stdev.) of Ratio and Rank. The sample period ranges from February 1984 to December 2018. EBP data end in September 2016. Due to EPB 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	1.933	1.000	5	3.304	1.000	2	1.226	1.000	7	1.991	1.000	5	1.000		4.750	2.062
DS q	1.970	1.019	6	4.072	1.232	8	1.183	0.965	6	2.253	1.131	7	1.087	0.119	6.750	0.957
TS q	2.003	1.036	7	3.605	1.091	6	1.139	0.929	5	1.823	0.916	1	0.993	0.085	4.750	2.630
TB q	1.876	0.971	4	3.402	1.029	5	1.102	0.899	4	1.844	0.926	2	0.956	0.057	3.750	1.258
DY q	2.119	1.096	8	3.969	1.201	7	1.355	1.105	8	2.605	1.308	8	1.178	0.099	7.750	0.500
HY-NEIO q-3:q	1.782	0.922	1	3.102	0.939	1	1.028	0.839	2	1.936	0.972	3	0.918	0.057	1.750	0.957
HYS q-3:q	1.824	0.944	3	3.316	1.004	4	1.086	0.886	3	1.951	0.980	4	0.953	0.051	3.500	0.577
EBP q	1.823	0.943	2	3.313	1.002	3	1.024	0.835	1	2.063	1.036	6	0.954	0.088	3.000	2.160

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.	2.630	1.000	2	4.087	1.000	2	1.566	1.000	3	2.161	1.000	2	1.000		2.250	0.500
HY-NEIO q-3:q	2.544	0.967	1	4.003	0.980	1	1.529	0.976	2	2.099	0.972	1	0.974	0.005	1.212	0.530
HYS q-3:q	2.834	1.078	4	4.224	1.034	3	1.614	1.030	3	2.341	1.084	3	1.056	0.028	3.250	0.500
EBP q	2.737	1.041	3	4.164	1.019	4	1.458	0.931	1	2.475	1.145	4	1.034	0.088	3.000	1.414

shown in Columns 3 and 4, 7 and 8, and 11 and 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 the HY-NEIO coefficient remains positive and significant, while the HYS loses its predicting ability, thus implying that HY-NEIO is an early predictor for monetary policies. We report similar results in Columns 7 and 8 and 11 and 12 for the federal funds rate and R&R, respectively. Note also that throughout all specifications in Columns 1 through 12, HY-NEIO is the only predictor that remains statistically significant. Combined, the results reported in Table 6 show that HY-NEIO is a strong early indicator of 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 examine forecasting errors of GDP growth and unemployment rate changes.

In Table 7 we report the root-mean-squared forecasting errors (RMSE) of one- or two-year 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 estimated from using HY-NEIO with those estimated from using other economic indicators including the HYS and the 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 forecasting when estimating regression coefficients. Specifically, in each quarter q, we first estimate regression coefficients of our forecasting models using the past ten 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 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 *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 other predictors in forecasting one- and two-year GDP growth and two-year unemployment rate changes. For exam-

Table 8
Lead-lag relations among flow components of various asset classes.

In this table we present the results of quarterly regressions of future NEIO and NSR flow components on their lags across various asset classes, over the next four quarters. For both panels, in Columns 1–4 we report the regressions of NEIO and NSR components to the high-yield (HY) and investment-grade (IG) categories on their lags and past cumulative returns on high-yield bond index returns (HYRET) and Baa-rated bond index returns (BaaRET). In Columns 5–8 we report regressions of the NEIO and NSR components on 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). In Columns 9–12 we report regressions of the NEIO and NSR components on the high-yield (HY) and government and money market mutual fund (GM) categories, controlling for past cumulative returns on high-yield bond index returns (HYRET) and the 3-month T-bill rate. The sample period ranges from February 1984 to December 2018. 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 in parentheses below the coefficient estimates. Given the persistence of the NSR components, the coefficient estimates and standard errors are corrected using the Amihud and Hurvich (2004) correction procedure.

	HY&IG $q+1$:$q+4$				HY&EQ $q+1$:$q+4$				HY&GM $q+1$:$q+4$			
	HY-NEIO (1)	HY-NSR (2)	IG-NEIO (3)	IG-NSR (4)	HY-NEIO (5)	HY-NSR (6)	EQ-NEIO (7)	EQ-NSR (8)	HY-NEIO (9)	HY-NSR (10)	GM-NEIO (11)	GM-NSR (12)
HY-NEIO q-3:q	0.291	2.078	0.221	2.266	0.031	1.355	0.251	1.193	−0.019	1.055	−0.182	0.083
	(1.80)	(4.67)	(2.88)	(3.85)	(0.16)	(2.71)	(5.51)	(3.45)	(−0.09)	(2.23)	(−3.45)	(0.15)
HY-NSR q-3:q	−0.109	0.261	−0.059	−0.402	−0.042	0.355	−0.052	−0.096	−0.003	0.352	0.030	−0.189
	(−2.04)	(1.72)	(−2.17)	(−2.06)	(−0.79)	(1.95)	(−3.71)	(−1.35)	(−0.04)	(2.81)	(2.53)	(−1.36)
HY-RET q-3:q	−0.033	−0.669	−0.020	−0.425	0.087	−0.100	−0.005	−0.065	0.013	−0.195	0.015	0.045
	(−0.65)	(−3.17)	(−0.97)	(−3.63)	(1.99)	(−0.77)	(−0.43)	(−1.25)	(0.27)	(−1.42)	(1.24)	(0.32)
IG-NEIO q-3:q	−0.651	−3.446	0.217	−2.046								
	(−1.62)	(−3.05)	(1.24)	(−1.96)								
IG-NSR q-3:q	0.139	0.698	0.036	0.835								
	(2.05)	(3.33)	(1.16)	(3.81)								
BAA-RET q-3:q	0.062	0.842	0.039	0.715								
	(0.87)	(2.13)	(0.96)	(2.84)								
EQ-NEIO q-3:q					0.351	−0.499	0.317	−1.225				
					(0.49)	(−0.26)	(1.75)	(−1.63)				
EQ-NSR q-3:q					0.129	0.390	0.036	0.883				
					(1.19)	(1.47)	(1.06)	(5.06)				
EX-RET q-3:q					−9.664	−16.300	−0.424	4.326				
					(−2.67)	(−1.68)	(−0.52)	(1.05)				
GM-NEIO q-3:q									−0.097	−1.124	0.215	−1.911
									(−0.20)	(−0.99)	(1.38)	(−1.55)
GM-NSR q-3:q									0.003	0.126	0.037	0.343
									(0.05)	(0.76)	(1.87)	(2.80)
T-bill q									−8.669	82.515	−4.053	205.750
									(−0.30)	(1.10)	(−0.69)	(3.61)
Adj R^2	0.150	0.531	0.311	0.545	0.256	0.439	0.497	0.642	0.049	0.461	0.396	0.513

ple, using HY-NEIO produces 6.45% (=1 − 3.102%/3.316%) and 6.37% (=1 − 3.102% / 3.313%) lower RMSEs relative to using the HYS and EBP, respectively, in forecasting two-year-horizon GDP growth. The only exception occurs when forecasting one-year unemployment rate changes, in which HY-NEIO is ranked second, being 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 HY-NEIO not only produces the smallest RMSEs but also has relatively low dispersion. For example, HY-NEIO has an average *Ratio* (*Rank*) of 0.918 (1.75) with a standard deviation of 0.06 (0.96), while the EBP has an average *Ratio* (*Rank*) of 0.954 (3.00) with a standard deviation of 0.088 (2.16).

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 add HY-NEIO, the HYS, and the 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, the results reported in Table 7 show that HY-NEIO presents strong out-of-sample predictability.

5. The fast-moving and “smart-money” behaviors of HY-NEIO

The previously reported results show that intra-family flow shifts into HY bond funds can serve as an early indicator of credit and economic cycles. Without knowing more about the identity of investors in HY funds, it is difficult to argue that these investors can simply forecast more accurately than any other investors. 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 “smart-money” behavior insofar as a trading strategy based on the signal from HY-NEIO is highly profitable.

In this section, we first present evidence that supports the idea that flow shifts captured by HY-NEIO involve fast-moving money, which is an early signal of future aggregate investor demand captured by slow-moving total net flows. Next, we show that HY-NEIO also behaves similarly to “smart” money, which can predict both stock and bond

Table 9
Regression of stock market return on HY-NEIO.
In this table we present the results of quarterly predictive regressions of excess stock market returns on HY-NEIO and other explanatory variables. In Columns 1–3 we report the regressions of the market excess return over the next quarter and in Columns 4–6 we report the regressions of the market excess return over the next four quarters. HY-NEIO is net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by end-of-previous-month assets. EQ-NEIO is the net exchanges (exchanges-in minus exchanges-out) of the equity category, normalized by end-of-previous-month assets (see Appendix A for more details). We also control for market excess returns over the past four quarters, 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). In the row marked by 1 SD HY-NEIO we show the one-standard-deviation effect of HY-NEIO on future market returns. The sample period ranges from February 1984 to December 2018. EBP data end in September 2016. 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 in parentheses below the coefficient estimates.

	$q+1$			$q+1{:}q+4$		
	(1)	(2)	(3)	(4)	(5)	(6)
EQ-NEIO *q-3:q*	−0.0104	−0.0079	−0.0026	−0.0124	0.0137	0.0148
	(−2.09)	(−1.08)	(−0.34)	(−0.74)	(0.60)	(0.81)
HY-NEIO *q-3:q*	0.0071	0.0090	0.0078	0.0187	0.0174	0.0169
	(2.97)	(3.38)	(2.88)	(2.56)	(2.65)	(2.34)
DEP *q-3:q*	−0.0266	−0.0824	−0.1780	−0.0755	−0.0894	−0.2712
	(−0.41)	(−1.42)	(−2.12)	(−0.51)	(−0.64)	(−1.91)
TS *q*		−2.169	−2.204		−3.568	−2.851
		(−2.53)	(−2.14)		(−1.71)	(−1.12)
DS *q*		−5.500	−0.549		−2.567	10.220
		(−1.97)	(−0.18)		(−0.47)	(1.32)
TB *q*		−1.003	−0.642		−2.549	−1.487
		(−2.62)	(−1.30)		(−2.39)	(−1.10)
DY *q*		3.948	3.885		12.020	11.390
		(2.47)	(2.38)		(2.38)	(2.55)
HYS *q-3:q*			0.007			0.018
			(0.33)			(0.44)
EBP *q*			−0.055			−0.142
			(−2.44)			(−2.52)
HYRET *q-3:q*			0.0004			−0.0007
			(0.36)			(−0.27)
1 SD HY-NEIO	2.26	2.86	2.49	5.95	5.56	5.38
Adj R^2	0.053	0.098	0.142	0.081	0.182	0.267

market returns and suggest that a trading strategy based on the signal from HY-NEIO is highly profitable. Lastly, we show evidence consistent with the idea that the predictive power of HY-NEIO is due to its predictive power for future investor demand.

5.1. HY-NEIO as an early signal of future investor demand

In Table 8, we examine whether HY-NEIO provides an early signal of 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. We are particularly interested in the predictability of persistent changes in aggregate demand that might last for several quarters. Consequently, we explore the predictive power of HY-NEIO over the next four quarters.[16]

In Columns 1–4 of Panel A we provide results from the regressions 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 Columns 1 through 4, 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-NSR, 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 that none of the other flow components, including past bond returns, can positively predict HY-NEIO, as shown in Column 1. Interestingly, HY-NSR marginally predicts future HY-NEIO but with a negative sign.

In Columns 5–12, we examine whether HY-NEIO can predict components of flows to the EQ and GM categories. Like the results presented in Columns 1–4, the results show that HY-NEIO predicts all other flow variables in the right direction for both the EQ and GM categories, as can be seen from positive and statistically significant coefficients on HY-NEIO in Columns 5–8 and the negative relation between HY-NEIO and GM in Column 11. In contrast, none of the other flow components can positively predict HY-NEIO, as shown in Columns 5 and 9. A VAR analysis of non-overlapping quarterly flows reported in the

[16] In the Internet Appendix we also report results of HY-NEIO predictive power over the next quarter.

Table 10
Regression of high-yield bond index returns on HY-NEIO.
In this table we present the results of quarterly predictive regressions of high-yield bond index returns on HY-NEIO. In particular, we show results for the next quarter ($q+1$), the next two quarters ($q+1$:$q+2$), and the next four quarters ($q+1$:$q+4$). The high-yield index is from Barclays. *Controls* include the term spread (TS), the default spread (DS), the 3-month T-bill rate (TB), and the dividend yield (DY). In the row marked by 1 SD we report the one-standard-deviation effect of HY-NEIO on future bond index returns. The sample period ranges from February 1984 to December 2018. 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 in parentheses below the coefficient estimates.

	$q+1$		$q+1$:$q+2$		$q+1$:$q+4$	
	(1)	(2)	(3)	(4)	(5)	(6)
HY-NEIO q-3:q	0.368	0.339	0.553	0.552	0.509	0.332
	(2.18)	(2.08)	(1.85)	(1.89)	(1.01)	(0.67)
DEP q-3:q		−0.005		−0.052		−0.100
		(−0.10)		(−0.72)		(−1.02)
1 SD	1.22	1.12	1.83	1.83	1.69	1.10
Controls	NO	YES	NO	YES	NO	YES
Adj R^2	0.043	0.151	0.041	0.276	0.015	0.429

Table 11
HY-NEIO versus total net flows during subsequent period.
In this table we report the quarterly regressions of HYS (Columns 1–3), the HY-Aaa spread (columns 4–6), the market excess return (Columns 7–9), the difference in log real GDP (Columns 10–12), and the difference in unemployment rates (Columns 13–15). 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. To evaluate the effect of future flows on HY-NEIO, for each of the dependent variables the first specification reports HY-NEIO coefficient without controlling for future flows (columns 1, 4, 7, 10, and 13). The sample period ranges from February 1984 to December 2018. 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 in parentheses below the coefficient estimates.

	HYS $q+1$:$q+4$			HY-Aaa $q+4$			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)	(11)	(12)	(13)	(14)	(15)
HY-NEIO q-3:q	0.112	0.080	0.072	−0.266	−0.108	−0.008	0.017	0.011	0.004	0.003	0.002	0.001	−0.137	−0.097	−0.051
	(4.70)	(3.75)	(2.92)	(−3.29)	(−1.63)	(−0.13)	(2.34)	(1.38)	(0.41)	(2.38)	(1.82)	(1.27)	(−2.99)	(−1.83)	(−1.08)
HY-FLOW $q+1$:$q+4$		0.016			−0.062			0.003			0.000			−0.019	
		(4.04)			(−3.68)			(2.02)			(1.27)			(−1.86)	
HY&EQ FLOW $q+1$:$q+4$			0.012			−0.068			0.005			0.000			−0.026
			(3.50)			(−4.93)			(2.80)			(2.02)			(−3.53)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.685	0.747	0.732	0.344	0.441	0.490	0.267	0.301	0.348	0.316	0.333	0.361	0.510	0.521	0.543

Internet Appendix also provides consistent and statistically significant results of longer horizon predictability.[17]

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 affects 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) equal 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 predictive 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.

In Table 9 we provide the results of the regression of future one- and four-quarter excess stock market returns on HY-NEIO, EQ-NEIO (intra-family flow shifts in EQ funds), the EBP, the HYS, and other control variables including 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. In comparison, EQ-NEIO negatively predicts the first-quarter returns, as shown in Column 1, but it shows no predictive ability for longer horizons, which is consistent with the results provided in Ben-Rephael et al. (2012), who argue that EQ-NEIO captures short-term investor sentiment.[18] Thus, the results show strong predictability of stock market

[17] The impulse response functions of the various flow components based on quarterly non-overlapping observations show a similar pattern. The results are reported in the Internet Appendix.

[18] Ben-Rephael et al. (2012) provide evidence that equity flows behave as “dumb money,” where quarterly EQ-NEIO is followed by a short-term stock market reversal.

Table 12
What explains HY-NEIO.

In this table we present the results of quarterly predictive time-series regressions of HY-NEIO measured over the next quarter (Columns 1–2) and next four quarters (Columns 3–4). In the table, each row represents a separate time-series regression controlling for lagged HY-NEIO and lagged returns. *Coef.* is the coefficient estimate of the explanatory variable of interest and AdjRSQ is the adjusted *R*-Squared from that regression. HY-NEIO is net exchanges (exchanges-in minus exchanges-out) of the high-yield corporate bond category, normalized by the end-of-previous-month assets. $\text{HYRET}_{q\text{-}3:q}$ is Barclay's high-yield excess bond index return over the previous four quarters. $\text{HYS}_{q\text{-}3:q}$ is the natural logarithm of the high-yield share over the previous four 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 the previous quarter, and over the previous four quarters. dA/A $_{q\text{-}3:q}$ is the difference in balance sheet assets between the end of quarter *q*-4 and the end of quarter *q* divided by 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 the change in log real GDP from the end of quarter *q*-4 to the end of quarter *q*. $\text{UR}_{q\text{-}3:q}$ is the difference between the unemployment rate at the end of quarter *q* and the end of quarter *q*-4. Fed-DRC $_{q\text{-}3:q}$ is the sum of federal discount rate changes over the previous four quarters. DiffVIX $_{q\text{-}3:q}$ 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. $\text{ExRET}_{q\text{-}3:q}$ is the cumulative excess return of the market index over the previous four quarters. The sample period ranges from February 1984 to December 2018. EBP data end in September 2016. 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 in parentheses below the coefficient estimates.

	HY-NEIO $q+1$		HY-NEIO $q+1{:}q+4$	
	Coef. (1)	AdjRSQ (2)	Coef. (3)	AdjRSQ (4)
HYS *q*-3:*q*	−0.395	0.075	−1.504	0.094
	(−2.06)		(−2.47)	
NBI *q*-3:*q*	−14.460	0.049	−59.694	0.033
	(−1.72)		(−1.84)	
dA/A *q*-3:*q*	−0.909	0.042	−2.963	0.022
	(−1.33)		(−1.28)	
HY Spread *q*	0.119	0.046	0.372	0.040
	(1.78)		(1.82)	
GDP *q*-3:*q*	−9.152	0.047	−51.015	0.068
	(−1.63)		(−2.01)	
UR *q*-3:*q*	0.148	0.045	0.887	0.066
	(1.55)		(2.15)	
Fed-DRC *q*-3:*q*	−0.099	0.043	−0.626	0.057
	(−1.21)		(−1.82)	
ExRet *q*-3:*q*	−2.768	0.114	−7.521	0.090
	(−3.68)		(−2.85)	
DiffVIX *q*-3:*q*	0.041	0.079	0.160	0.134
	(3.19)		(2.72)	
Controls				
HY-NEIO *q*-3:*q*	YES		YES	
HYRET *q*-3:*q*	YES		YES	

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 the high-yield bond index returns up to the next four quarters. The results reported in Columns 1 through 4 indicate that HY-NEIO positively predicts future bond market returns up to the next two quarters.

In untabulated results, we construct a monthly trading strategy that involves investing in the Barclays HY corporate bond index based on HY-NEIO and compare its Sharpe ratio with a buy-and-hold strategy that invests 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 monthly HY-NEIO at time t, $R_{HY,t+1}$ is the return on the Barclays HY index, and $R_{F,\,t}$ is a one-month Treasury bill rate. For our sample period, we find that the annualized Sharpe ratio of this strategy is 0.98, whereas the annualized Sharpe ratio of the buy-and-hold strategy is only 0.60.

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). There is a growing body of literature that suggests that trading decisions made by certain groups of individual investors can carry valuable information (e.g., Kaniel et al., 2008; Kelley and Tetlock, 2013, 2017). More importantly, unlike the 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; and the investor base in high-yield funds is distinctly different from the investor base in equity funds. Thus, portfolio choices made by HY investors could provide a good signal of future investor flows and serve as an early indicator of future demand changes.

5.3. Predictive power of intra-family flow shifts and future total net flows

In Table 11, we examine the extent to which the predictive power of HY-NEIO operates through its predictive 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 with regard to future investor demand, HY-NEIO is not expected to have predictive 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.

In Table 11 we provide the estimation results from the regressions of 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 predictive ability of HY-NEIO. To ease the comparison of the coefficient estimates, for each of the dependent variables we include the baseline results first.

Specifically, Columns 1–3 show 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 4 through 15, however, we find that future flows tend to absorb the explanatory power of HY-NEIO. For example, Columns 4–6 indicate that controlling for future flows reduces HY-NEIO coefficient estimate from −0.266 (the baseline) to −0.008, 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. The effect of future flows on GDP and UR is impor-

Table 13
Regressions of credit and business cycle variables on predicted and unpredicted components of HY-NEIO.
In this table we report the results of regressing credit and business cycle variables on predicted HY-NEIO and unpredicted HY-NEIO. We obtain the predicted component of HY-NEIO (PRED HY-NEIO) by regressing *HY*-NEIO $_{q-3:q}$ on the full set of economic variables defined in Table 12 and using the fitted values from the regressions as the predicted component. The unpredicted component (RESID HY-NEIO) is the residual of the regressions. *Controls* refers to full set of control variables for each of the dependent variables. For example, see Column 6 (Column 8) of Panel A of Table 5 for GDP-1Y (GDP-2Y). Standard errors are calculated using Newey–West (1987) correction, where the number of lags is based on the number of overlapping observations. *t*-statistics are reported in parentheses below the coefficient estimates.

	HYS-1Y	RFY-1Y	HY-Aaa-1Y	GDP-1Y	GDP-2Y	UR-1Y	UR-2Y	DCR-2Y	MktRf-1Y	HYRET-6M
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PRED HY-NEIO q-3:q	0.1073	0.0125	−0.1723	0.0010	0.0005	−0.0147	0.0150	0.2153	−0.0075	0.1429
	(2.73)	(1.69)	(−1.32)	(1.03)	(0.27)	(−0.42)	(0.15)	(2.43)	(−0.73)	(0.33)
RESID HY-NEIO q-3:q	0.1035	0.0128	−0.3743	0.0036	0.0051	−0.1373	−0.2276	0.2458	0.0259	0.8160
	(4.32)	(2.47)	(−2.77)	(3.67)	(3.24)	(−3.05)	(−3.08)	(2.87)	(3.12)	(1.87)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

tant at long horizons, consistent with the timing reported in Table 5 and Figs. 5 and 6. Overall, Table 11 provides consistent evidence that HY-NEIO's predictive ability is connected to its ability to predict aggregate future demand.

5.4. What explains HY-NEIO?

HY-NEIO is based on investor flows, thus, it helps trace the origins of the credit boom to an increase in investor demand. In this section, we examine which factors can explain future HY-NEIO, to shed light on lead-lag relationships between HY-NEIO and shifts in aggregate demand.

In Table 12, we regress future HY-NEIO in quarter $q+1$ and over quarters $q+1$:$q+4$ on the HYS, returns on the stock market and high-yield bond index, and VIX as well as other common variables in the literature that might explain investor portfolio choices.[19] Each row represents a different model, where we control for lagged HY-NEIO and past returns, and report the coefficient of interest together with the adjusted *R*-Squared.

We find that HY-NEIO does not tend to follow credit boom (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 to the credit market. We further find that the HYS negatively (not positively) predicts HY-NEIO, which suggests that overheating in credit conditions does not lead HY-NEIO. In other words, when the HYS is elevated, investors in high-yield bonds 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. HY-NEIO responds negatively 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 predict future HY-NEIO, but the signs of the coefficients imply that investors tend to shift to HY funds when market conditions are poor in general (i.e., low stock market returns and increases in VIX). This result suggests that HY-NEIO is a useful early indicator for turning points in economic cycles.

In sum, the results reported in Table 12 show that HY-NEIO does not positively (negatively) respond to past positive (negative) economic or credit conditions. Rather, the investor behavior that is captured by HY-NEIO seems to anticipate the cycle rather than following it.

5.5. Unexpected versus expected components of HY-NEIO

The results provided in Table 12 show that several macroeconomic factors can predict future intra-family flows. A natural question follows: is the predictive ability of HY-NEIO driven mainly by these factors or is it driven by the unexpected component of HY-NEIO that can be attributed to idiosyncratic shifts in investor demand?[20] In this section, we decompose HY-NEIO into expected and unexpected components based on macroeconomic factors and examine the extent to which the predictive power of HY-NEIO stems from the unexpected component. We obtain the unexpected component in the form of residuals from the multiple regressions of future HY-NEIO on all the independent variables that we consider in Table 12. We then rerun the predictive regressions of the credit and business cycle variables using these expected and unexpected components.

Table 13 provides the regression results, where we report results obtained using longer-horizon dependent variables.[21] Importantly, regardless of the horizon used, we find that the predictive power of HY-NEIO is driven mostly by its unexpected component. Across all the ten specifications we consider, we find that the coefficient estimates on the unexpected component are statistically significant at the conventional levels, whereas the expected component is statistically significant in only two cases. Overall, these results show that idiosyncratic investor demand shifts that are unrelated to past macroeconomic variables serve as a useful indicator of future credit and economic cycles.

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[19] We use the VXO,which is based on the implied volatility of the S&P 100 options, available from 1986 and highly correlated with the VIX.

[20] Ferson and Kim (2012) use principle component analysis to construct systematic common factors based on mutual fund flows. They find that these factors can be predicted by market conditions and macroeconomic variables, which suggests that predictability in the flows can be driven by these variables.

[21] Results using quarterly non-overlapping dependent variables are reported in the Internet Appendix.

6. Robustness checks

We perform a comprehensive set of robustness checks. To conserve space, we report the results together with their detailed discussions in the second part of the Internet Appendix. First, we alleviate concerns regarding statistical inference using overlapping observations by employing non-overlapping annual regressions and reporting bootstrap-simulated standard errors. Second, we show that HY-NEIO beats other flow components across various asset classes, by running horseraces against one another. Third, we show that the predicting power of HY-NEIO tends to increase in our sample period but it is not concentrated in some particular sample period. We also verify that our results are not driven by the 2007–2008 financial crisis. Fourth, we employ first differences in total net flows instead of levels to examine whether changes in total flows can be informative of future credit cycles. We find that, while changes in total net 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 et al., 2017). Recently, there is a developing narrative whereby investor demand is a key driver of fluctuations in credit markets and future economic activities. In this paper, we offer a direct measure of investor demand using investors' portfolio choices of high-yield bond funds, which can serve as a leading indicator of both credit and business cycles. Our measure thus captures early shifts in investor 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 RFY 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 high-yield and default credit spreads as well as Gilchrist and Zakrajšek's (2012) 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 the EBP. It also forecasts changes in monetary policy.

Positioning our measure along the timeline of credit and business cycles (as described in Lopez-Salido et al., 2017), our measure shows up a year in advance before the onset of a cycle. Thus, it provides early signs of the evolution of a cycle, which should be taken into consideration by policymakers.

Appendix A

ICI mutual fund categories.

In this appendix we report Investment Company Institute (ICI) statistics for 33 mutual fund investment categories (asset classes). The sample period ranges from January 1984 through December 2018, a total of 419 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 bonds 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) fraction of assets in the category with respect to the total assets in all ICI categories.

			Category assets/total ICI assets			
Asset class	Category	*N*	Avg	Median	Min AR	Max AR
Equity						
Aggressive Growth	1	419	5.60	5.52	2.78	9.19
Growth	2	419	12.57	13.83	5.69	21.68
Growth and Income	3	419	13.13	13.49	7.31	19.19
Income Equity	4	419	1.64	1.47	0.97	2.93
Sector	5	419	1.77	1.98	0.10	3.73
Emerging Markets	6	337	0.96	0.53	0.00	2.22
Global Equity	7	419	2.72	2.94	1.07	4.34
International Equity	8	419	4.19	3.77	0.25	9.27
Regional Equity	9	347	0.51	0.42	0.25	1.23
Corporate Bond						
Asset Allocation	10	347	0.45	0.47	0.17	1.03
Balanced	11	419	2.44	2.71	0.71	3.27
Flexible Portfolio	12	419	1.52	1.66	0.18	2.79
Income Mixed	13	419	1.70	1.90	0.51	2.58
Corporate - General	14	419	0.95	0.91	0.46	1.36
Global Bond - General	15	419	0.75	0.44	0.01	2.11
Strategic Income	16	419	4.32	2.90	0.63	10.88
World Bond	17	347	0.36	0.19	0.02	1.08
Corporate - Short Term	18	347	1.11	0.93	0.55	2.04
Corporate - Intermediate	19	347	0.89	0.83	0.56	1.40
Global Bond - Short Term	20	347	0.21	0.14	0.03	1.45
Mortgage Backed	21	419	1.79	1.12	0.51	5.54
High Yield	22	419	1.99	1.91	1.01	4.14

(*continued on next page*)

Appendix A (*continued*)

Asset class	Category	*N*	Category assets/total ICI assets			
			Avg	Median	Min AR	Max AR
Muni Bond						
National Municipal Bond - General	23	419	3.35	2.32	1.61	7.00
State Municipal Bond - General	24	419	2.37	1.85	0.80	5.36
National Municipal Bond - Short Term	25	347	0.55	0.59	0.18	1.09
State Municipal Bond - Short Term	26	347	0.10	0.07	0.03	0.26
Government Bond						
Government Bond - General	27	419	2.18	0.56	0.27	12.30
Government Bond - Intermediate	28	347	0.48	0.32	0.16	1.33
Government Bond - Short Term	29	347	0.56	0.36	0.20	2.18
Money Market						
National Tax-Exempt Money Market	30	419	3.28	2.66	0.49	8.68
State Tax-Exempt Money Market	31	419	1.08	1.20	0.13	2.35
Taxable Money Market - Government	32	419	7.71	6.90	3.84	16.10
Taxable Money Market - Non-Government	33	419	17.82	16.35	2.30	43.23

Appendix B

Sales, redemptions, exchanges-in and exchanges-out.

In this appendix we provide 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 asset classes within the same fund families. SR reports 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	4121	1789	2332	1368	667	701	3033	110,102
High-Yield	2/28/1998	3742	1795	1947	884	681	203	2151	114,123
High-Yield	3/31/1998	4281	2312	1969	1251	1073	178	2147	117,564
High-Yield	4/30/1998	3254	2117	1138	896	1197	−301	837	118,986
High-Yield	5/31/1998	3169	1810	1359	923	798	125	1484	120,342
High-Yield	6/30/1998	3282	2093	1189	884	986	−101	1088	121,390
High-Yield	7/31/1998	3365	1967	1398	1398	950	448	1846	124,234
High-Yield	8/31/1998	2704	3824	−1120	742	3008	−2266	−3386	111,124
High-Yield	9/30/1998	2657	2177	480	1065	1218	−153	327	110,667
High-Yield	10/31/1998	2866	2321	545	1480	1646	−166	379	108,296
High-Yield	11/30/1998	5227	1892	3335	2077	710	1367	4702	119,841
High-Yield	12/31/1998	3206	3151	55	952	2011	−1059	−1005	117,444
Total		41,872	27,247	14,626	13,920	14,943	−1023	13,602	

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