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Abstract

Financial intermediaries play a key role in the formation of asset prices. More specifically, the increasing importance of non-bank financial intermediaries has raised new questions about the risks that hedge funds pose to the financial system. We focus on the role that changes in hedge fund exposures play in driving U.S. Treasury prices and the yield curve. Using confidential hedge-fund data from the SEC's Form Private Fund (PF), we calculate hedge funds' aggregate, net Treasury exposures, and their fluctuations over time. We find economically significant and consistent evidence that changes in aggregate hedge fund exposures are related to Treasury yield changes. In the cross-section of hedge funds, we also show that particular strategy groups and lower-levered hedge funds display a larger estimated price impact on Treasuries. Finally, asset pricing tests show evidence of positive risk compensation associated with shifts in hedge fund Treasury demand.

Keywords: Hedge funds; price impact; U.S. Treasury market.

JEL Classification: E43, G12, G20, G23

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1 Introduction

Financial intermediaries play a sizeable role in the macroeconomy, directly affecting firms' leverage and investment behavior, and amplifying economic dynamics across booms and recessions (e.g., Bernanke, Gertler, and Gilchrist (1999)). However, the channels through which intermediaries affect asset prices are less understood. Recent literature on intermediary-based asset pricing (e.g., He and Krishnamurthy (2013); Adrian, Etula, and Muir (2014)) discusses the idea that the net worth or financial constraints of intermediaries matter in asset classes where such institutions act as marginal agents. Risk premia on specific assets are determined by the degree to which banks, mutual funds, pension funds, broker-dealers, and other non-bank financial intermediaries (NBFI) transact and display demand for them. In this study we focus our attention on another prominent type of NBFI, *hedge funds,* and ask how their demand for safe assets affects the valuation of a central asset in the global marketplace, U.S. Treasury securities.

As leveraged and well-informed investors, hedge funds impound information into prices through their trades, rendering prices more informative and the market more efficient. At the same time, recent events have raised questions about whether hedge funds increase systemic risk. For example, as the COVID-related financial turbulence hit U.S. markets in March 2020, a flight to quality into the most liquid safe assets led to Treasury market volatility that widened the Treasury cash-future basis. This widening forced several relative value hedge funds to unwind their positions, causing additional market disruptions.[1] The financial press has also suggested that risk parity and short volatility funds, through their dynamic rebalancing, cut back on their positions in response to market volatility. Such deleveraging may have exacerbated the market turmoil.[2]

Although there is indirect evidence of selling pressure in the Treasury market during March 2020, evidence on the general relation between hedge-fund exposures and Treasury yields using public or commercially available data has been harder to come by. In this paper, we tackle this issue by directly estimating the price impact of hedge funds in Treasury markets. Using information related to hedge funds' direct holdings from the SEC's Form Private Fund (PF), we compute the total notional exposures (i.e., cash bond and derivative positions) that hedge funds have to U.S. Treasury markets and their fluctuations over time. Further, we exploit the rich cross-sectional heterogeneity of these data to compare the

[1] Since March 2020, research on the basis trade has ballooned. See Schrimpf, Shin, and Sushko (2020), Barth and Kahn (2021), and Kruttli, Monin, Petrasek, and Watugala (2021).

[2] For example, an article in the Wall Street Journal on April 1, 2020, reported, "Some of the most chaotic swings in markets were exacerbated by investors forced into selling by pre-programmed trading strategies that react to spikes in volatility."

estimated price impact across funds that implement different types of investment strategies.

Based on monthly analysis dating from 2013 to the fourth quarter of 2020, we find economically significant and robust evidence that changes in hedge-fund exposures are related to Treasury yield changes. A one standard deviation increase in the net growth of Treasury exposures, which translates to a $41 billion monthly increase in hedge fund net exposures, is associated with a 6.2 basis point decline in five-year bond yields. The size of this estimate is not sensitive to controlling for well-known macroeconomic drivers of the yield curve, such as economic growth and inflation, and exists at various maturities. It is also robust to controlling for the valuation effects of yields on exposures and changes in other financial entities' Treasury exposures.

Moreover, we find differences in the estimated price impacts across funds that trade different strategies and use different amounts of leverage. At the strategy level, the net exposure changes of managed futures and multi-strategy funds have the most significant price impact and relative value funds have a more negligible impact. Similarly, funds with ex-ante higher balance sheet leverage have the weakest price impact in Treasury markets. These results are surprising from the canonical risk viewpoint. High leverage levels, all else equal, could lead to a more significant price impact because the positions are larger. Instead, we find the opposite.

In the paper's final part, we more directly relate our work to the empirical literature on intermediary based asset pricing (e.g., He, Kelly, and Manela (2017)). Using conventional asset pricing methods, we treat hedge fund exposures as a possible risk factor to test whether it is priced in the cross-section of Treasury returns. While betas to hedge fund exposures and the associated price of risk are positive, we find that the price of risk ("lambda") is imprecisely estimated, in particular. The statistical insignificance of the hedge fund lambda is likely related to the weak power of the statistical tests due to the limited sample size in the time dimension. The inflation lambda suffers from a similar problem unless we extend the sample back to the 1950's. Regardless, the positive lambda associated with hedge fund Treasury exposures is consistent with hedge fund Treasury demand as a state variable important for pricing Treasuries.

In the rest of this section, we discuss related research on hedge funds and how our paper builds on that research. We describe the SEC Form-PF data in Section 2. Section 3 provides regression evidence on hedge-fund price impact in the Treasury market. Section 4 examines whether hedge fund Treasury exposures are a priced risk factor. We summarize our conclusions in Section 5.

Related Literature

Our paper is related to two broad strands of research – one on the price impact of asset managers, and the other on hedge fund characteristics. What differentiates our paper from other research is our focus on hedge fund activity in the Treasury market and our use of direct asset class exposures, both long and short, from the SEC Form PF data to study this question.

Shleifer (1986) is one of the earlier works in the market price impact literature that focuses on the positive abnormal return of stocks following inclusion into the S&P 500. He finds evidence that measures of stock buying by index mutual funds are associated with these abnormal returns. Lakonishok, Shleifer, and Vishny (1992) examine end-of-quarter holdings data of pension funds and connect cross-manager flows with herding measures. They find first that managers do not generally herd (i.e. follow each other) and second that measures of excess demand by institutions are not greatly related to price changes in the underlying stock. Wermers (1999) extends the herding (or "crowding") concept to the mutual fund space and finds that there is relatively low levels of herding for the average stock but greater levels of it for small stocks. An additional contribution that relates to price impact, shows that stocks herded into outperform those herded out of. Relative to Lakonishok et al. and Wermers our analysis focuses squarely on the Treasury market and uses hedge fund data. Using modern day data from the mutual fund industry, Coval and Stafford (2007) show that mutual funds that experience large outflows reduce their positions, creating negative price pressure on securities they hold. On a somewhat related topic, Frazzini and Lamont (2008) show that mutual fund flows, above and beyond some average value, signal negative returns in the future. This indicates that mutual fund flows can be considered "dumb money."

In a recent and very influential paper, Koijen and Yogo (2019) design an asset pricing model that examines the portfolio demand for heterogeneous institutions with short-sale constraints (including hedge funds). They take the model to SEC Form 13F data that provide quarterly holdings of a number of different institutions, including hedge funds. Using the model, they estimate the price impact of demand shocks and show that it has reduced in magnitude over time. There are a few ways in which our work is different than Koijen and Yogo. First, our use of Form-PF data gives us direct asset class exposures (both long and short) on a monthly basis which helps identify market impact; Form 13F only captures the long equity side. Second, our focus on Treasury exposures (as opposed to equities) distinguishes it substantially from the literature. Finally, we use balance sheet information only available through Form PF to characterize the relationship between price impact and various fund characteristics.

As we test price impact across multiple, sorted groups of hedge funds, our work also speaks to the literature on hedge fund characteristics. Ang, Gorovyy, and van Inwegen (2011) discuss cross-sectional and time series patterns of hedge fund leverage going back to the period of 2004 through 2009. Their data is taken from a proprietary data-set from a fund of hedge funds. They find that changes in fund leverage are predictable by aggregate factors rather than fund-level characteristics. Bali, Brown, and Caglayan (2014) find that cross-sectional dispersion in hedge fund returns are explained by dispersion in fund-level betas to measures of macroeconomic uncertainty. This relationship is robust to a number of different uncertainty measures. Finally a recent paper by Barth, Hammond, and Monin (2020) examines the relationship between leverage and risk-taking in hedge funds. The authors find a negative association between return betas and leverage. In our work we also derive similar findings as we find that the price impact of highly levered funds is insignificant relative to lowly-levered funds.

2 Data

Because hedge funds (and their strategies) are private, monitoring their positioning data is challenging for policymakers and researchers. To partly overcome this challenge, the Dodd-Frank Act mandated that SEC-registered private fund advisers (private equity, real estate, hedge, and liquidity funds) report various income and balance sheet information for systemic risk assessment. In particular, the data collected through SEC Form-PF help our intended study because it includes long and short exposure information on US Treasury and related derivative assets. Exposure data are available monthly at the fund level, which we aggregate to obtain industry-wide series of asset-class exposures. We focus our analysis on the largest of hedge funds, also known as qualifying hedge funds, as these funds are required to report more frequently.[3]

In Figure 1, we display the hedge fund US Treasury exposures aggregated across qualifying hedge funds, from long and short positions. All data including these are on a monthly frequency from January 2013 through December 2020. As of December 2020, long and short positions amounted to roughly \$966 and \$623 billion, respectively. It is important to note that "notional exposures" can correspond to both the holdings of US Treasury securities (cash bonds) or exposures to U.S. Treasury (UST) linked derivatives (futures and swaps). As the latter category does not require significant expenditure of balance sheet liquidity, relative to purchasing Treasury bonds outright, many hedge funds choose to take part in

[3]Qualifying Hedge funds are those that have at least \$500 million in net asset value (NAV) as of the last day prior to a fiscal quarter. Naturally, the count and distribution of qualifying hedge funds shift over time as NAV values fluctuate.

derivative markets.

The figure also shows an upward trajectory in the gross notional exposures of Treasuries, where gross exposures (sum of long and short positions) grow to a peak in February 2020. Coincident with the collapse of financial markets in the following month, total exposures drop dramatically both on the short and long end, and do not recover by the end of the year. Another interesting pattern that is apparent is the strong correlation between long and short exposures. One reason for this is the bond basis trade in which some relative value (RV) hedge funds participate. While it is not the focus of this paper, the bond basis trade goes long cash Treasury bonds and short Treasury futures. Hence, any movements in aggregate trade size, upwards or downwards, would lead to short futures and long cash bond exposures moving in tandem. Intuitively, the large decline of the gross exposures in March aligns with the evidence of declines in basis trading, as discussed in Barth and Kahn (2021) and Kruttli et al. (2021).

The fact that both long and short exposures move together might suggest that net dynamics will be relatively constant. However, it can be shown that there is strong time-variation (and a similar upwards pattern until early 2020) in net positions. Movements in net positions can be partly attributed to typical strategy re-balancing across non-RV funds, such as managed futures funds that execute momentum-based strategies.

Changes in Hedge Fund Exposures

In the top two panels of Table 1 we provide summary statistics on hedge fund variables that will be actively used in our empirical analysis. Throughout this paper, we will focus on changes in exposures as they both statistically account for the non-stationarity in our level series and represent an economically meaningful quantity. Changes in the levels of exposures can be interpreted as an imprecise measure of flows into or out of Treasury markets.[4] As our study seeks to examine the price impact of movements in hedge fund demand, the change measure is appropriate.

In the top panel, we show that movements in long, short, and net exposures are on average positive with standard deviations of \$49, \$36, and \$41 billion monthly. As the change in net exposures gets closer to measuring movement in hedge fund demand, this variable will be of key interest to us. We also show in the table that a total of 1,639 funds contributes to the Net change measure, in the full time series, with an average of 628 funds per month.

In the second panel, we decompose the net change measure into specific strategy subtypes, as these strategy groupings will play a role later on in our analysis. In the Form-PF

[4] The imprecision of this variable as a flow measure is because it also includes a price component (it is not a pure shift in hedge fund demand). We try to correct for the price component in a later section.

data, advisers self-report fund-level strategies. The major groups that appear are multi-strategy, relative value, macro-based, managed futures, and equity. Across all of these five groups, the largest number are classified as multi-strategy funds (441 out of 1639), followed by equity (323) and relative value (220). Regarding the volatility of net exposure movements by strategy, it seems that multi-strategy funds also contribute the most ($31 billion per month).

Bond Yield Data

As our focus is on the US Treasury asset class, we use month-end, zero-coupon bond yields from the Federal Reserve Board, estimated using the methodology in Gurkaynak, Sack, and Wright (2007). We use this dataset because it provides bond yields at 30 different maturities (1Y - 30Y) and focuses on the basic building block of bond pricing the zero-coupon discount curve. Studying the curve is important because it is directly related to the assets of interest and is a fundamental instrument that enters the pricing of all risky assets by discounting future cash flows. It is important to note that all 30 maturities are not necessarily traded and are instead imputed from the daily estimation of a term structure model fitted to actively traded Treasury bonds.[5]

In the bottom panel of Table 1 we display summary statistics of our key dependent variable of interest, maturity-specific changes in the level of bond yields. The data presented here are in basis points and measure changes from January 2013 through December 2020, the same period as hedge fund data are available. On average bond yields decrease over this time sample (e.g., the 5Y security decreases -.38 b.p. per month). However, the standard deviation is fairly high at roughly 20 basis points per month, across most maturities. In the next section we try to explain some of these monthly movements via hedge fund Treasury exposures.

3 Treasury Market Impact

In this section we focus on the relationship between hedge fund U.S. Treasury exposures and movements in bond yields. Traditionally, the literature on hedge fund fire sales and market impact focuses on forced de-leveraging during a crisis event. For example, the seminal paper by Brunnermeier and Pedersen (2008) discusses a feedback mechanism between funding liquidity and market liquidity. Shocks to funding conditions can transmit to financial markets as asset managers (and other participants) are forced to de-leverage. The resulting, potentially large reductions in asset prices can subsequently lead to even greater stress

[5]Furthermore, on-the-run and first off-the run security prices are not used in the estimation which suggests that the term structure data we use should be interpreted as an "off-the-run term structure."

in funding markets. Beyond the Global Financial Crisis period, a key example of such an episode was the recent collapse of Archegos Capital Management. Lending intermediaries that were exposed to Archegos' default risk through total return swaps were forced to sell off sizable quantities of risky securities, leading to steep losses both in the underlying securities as well as the system.

In our paper we interpret our hedge fund exposure measures differently. As opposed to forced de-leveraging in a crisis episode, it is well known that systematic hedge funds engage in various strategies that re-balance as a function of current financial market data and other trading signals. These type of strategies often re-balance frequently (weekly or bi-weekly) with lower magnitudes of position change. Commonly discussed strategies such as smart beta, risk parity and short volatility, momentum trading, and merger or convertible arbitrage all rebalance to optimize cross-portfolio hedging and minimize transaction costs relative to overall gains on the trade. As we discuss the effects of hedge fund demand or trading, we believe that our results will more closely align itself with this form of "lower frequency price impact." Reinforcing this very point, we will later show that our price impact estimates are actually weakened by the March 2020 episode – an event where hedge funds dramatically shift away from Treasury assets over the course of a few days.

3.1 Baseline Results

Our main specifications examine whether movements in hedge fund demand have a contemporaneous relationship with movements in US Treasury bond yields. We start with a linear regression model

$$\Delta y_t^m = \beta_0 + \beta_{HF} \Delta HF_t^* + \beta_X' X_t + \varepsilon_t^m \tag{1}$$

where Δy_t^m is the monthly change in maturity m's bond yield. On the right hand side ΔHF_t^* is the raw monthly change (the first difference) in a hedge fund exposure variable (long, short, or net). Finally, X_t is a set of controls that include the growth rates of the real industrial production index, PCE inflation index, and the total debt outstanding. As discussed in Ang and Piazzesi (2003), macroeconomic factors, particularly inflation, are priced in the term structure of interest rates. The outstanding supply of debt can naturally have an impact on bond yields all else equal. More generally, our inclusion of controls helps us work towards isolating the effects of hedge fund positions on bond yields.

When looking at the long and net variables, we expect that $\beta_{HF} < 0$ as an increase in hedge fund demand, all else equal, would increase bond prices and reduce bond yields. In Table 2, we present results largely in line with these hypotheses. The results are split into three panels, which discuss the effects of long, short, and net growth (from left to right) on 2Y, 5Y, and 10Y yields (within a panel). Coefficients are scaled to represent the basis point effect of a 1 standard deviation movement. For example, a 1 standard deviation movement in net growth is associated with a 6.19 basis point drop in the 5Y bond yield. Overall, the growth rate of long Treasury exposures seems to be linked with negative and significant effects on longer-term bond yields. Most importantly, net growth is significant across all the regressions, which is a result that will repeat itself. All standard errors account for heteroskedasticty and auto-correlation in residuals.

To put these estimates into perspective, a standard deviation movement of monthly 5Y bond yield changes is roughly 20 basis points. Hence, a typical movement of hedge fund demand amounts to a non-trivial (yet non-extreme) movement of bond yields – roughly a .25 standard deviation movement of bond yields. Additionally, when we compare the movement of net growth with that of inflation, we see the coefficients are roughly similar in absolute value (6.2 vs. 6.1 b.p.). Comparing the estimate associated with hedge fund exposures with that of inflation is also a good benchmark. Research has established that inflation has an out-sized effect on nominal bond yields.

3.1.1 Reverse Causality

Due to the frequency of the data, and other omitted variable issues, it is difficult to conclude that the results are causal (i.e., that hedge fund demand spikes cause movements in bond yields). However, we try to get closer to a causal statement by tackling another issue – reverse causation. The hedge fund position data we work with are in market value terms, which suggests that downward movements in yields (the outcome variables) might be mechanically increasing the market value of hedge fund exposures. If that were the case, the negative relationship we observe in the regressions might come from the opposite direction.

As we do not have the exact maturities, prices, and positions of the U.S. Treasuries that underlying hedge funds trade, we examine the robustness of our results using two different approaches. First, we scale our growth variables by the return on a five-year Treasury security.[6] More specifically, we define a new variable, $\Delta HF_t \equiv \frac{\Delta HF_t^*}{R_t^{5Y}}$, where R_t^{5Y} is the synthetic return of holding a 5Y bond for a month and ΔHF_t now represents an adjusted growth rate. The rationale behind these modifications is that the adjusted growth rate will measure changes in positions above and beyond price movements.[7] The top panel of Table

[6] The underlying assumption is that the average duration of hedge funds' Treasury portfolios is five years. This is consistent with evidence presented later regarding the maturity-specific impact.

[7] To compute the return, we use the zero-coupon structure of bond yields to take the ratio of successive monthly prices. The synthetic return is given by $R_t^{5Y} = P_t^{5Y}/P_{t-1}^{5Y} = \exp\left(-5 * \left[y_t^{5Y} - y_{t-1}^{5Y}\right]\right)$.

3 displays the results of this modified regression. We find that scaling hedge fund exposures by the return on the 5Y bond does not substantively change the coefficient values.

Our second approach modifies the net exposure growth variable slightly differently, assuming that hedge funds' average Treasury duration is five years. We decompose the total position as $HF_t^* = P_t^{5Y} \times Q_t^*$, where Q_t^* is the approximate face value of outstanding Treasury assets and P_t^{5Y} is the price of a zero coupon five-year bond (the same that is used to compute the return in the previous approach). With this definition of Q_t^*, we define: $\Delta HF_t \equiv Q_t^* - Q_{t-1}^* = \frac{HF_t^*}{P_t^{5Y}} - \frac{HF_{t-1}^*}{P_{t-1}^{5Y}}$. We perform this procedure separately for the long, short, and net positions and implement these new variables in our basic regression specifications. The results are presented in the second panel of Table 3. We find that this form of price adjustment has a slightly sharper effect on the net growth elasticities. The absolute sensitivities of 5 and 10-year yields shrink slightly from 6.2 to 4.7 and 5.8 to 4.3 basis points. However, all results are significant, and the longer-term yields are significant at the 1% level.

In summary, the baseline results are robust to different methods of controlling for simultaneity bias. No method is perfect, however, and moving forward in this paper, we only use the raw hedge fund exposure changes scaled by five-year returns (first approach from above) as they seem to be stronger.

3.1.2 Market Impact across Maturities

In the results above we focused our attention on three maturities. We examine similar effects across all 30 maturities in our bond yield dataset in this discussion. Specifically, we examine a separate regression for each maturity, like the one in Table 3, and solely focus on movements in net exposures as they are economically more meaningful. It will be of the form:

$$\Delta y_t^m = \beta_0 + \beta_{HF} \Delta HF_{net,t} + \beta_X' X_t + \varepsilon_t$$

where the explanatory variable of interest is the adjusted net growth measure. Hence in total there will be 30 regressions. Figure 2 displays the results from these regressions with $\hat{\beta}_{HF}^n$ and standard error bounds reported for each maturity. In the top panel, The blue line shows the point estimates of this regression in basis points, while the grey band reflects the 95% standard error band surrounding the estimates. In the bottom panel, these coefficients are scaled by the volatility of each maturity's movements in bond yields.

The figure clearly displays that the association between hedge fund Treasury demand and bond yield movements is significant and robust across various maturities. Moreover, the coefficient value (blue line) is consistently negative and the standard error bounds rarely cross zero. The point estimates are quite similar across maturity which might be attributable to the low-dimensional nature of bonds (e.g., level, slope, curvature). That being said, it is also worth observing that the coefficient value increases in absolute value around the 4 - 7Y horizon. One way to interpret this finding is that hedge funds tend to take positions closer to this medium-term horizon. Of course, this interpretation is not perfectly identified, and more granular work is needed to tease out these effects.

3.1.3 Expected Short Rates vs. Term Premia

Under the Expectations Hypothesis (EH), longer term bond yields are solely a function of expected future short rates (forward rates). However in the data, because the EH does not hold (see Campbell and Shiller (1991)), there is an additional term premium component that captures the expectations of future excess returns. More precisely, the n-period bond yield at time t can be broken up into:

$$\begin{aligned} y_t^n &= \frac{1}{n}\sum_{i=1}^{n} \mathbb{E}_t\left[y_{t+i-1}^1\right] + \frac{1}{n}\sum_{i=1}^{n} \mathbb{E}_t\left[r_{t+i}^{n+1-i}\right] \\ &= ES_t^n + TP_t^n \end{aligned} \tag{2}$$

A natural question arises from this decomposition. Given hedge fund exposures have a relationship with movements in *total yields*, which component do hedge fund exposures affect the most? We answer this by using the flexible term structure model estimated in Adrian, Crump, and Moench (2013) and its model output, which decomposes yields into expected short rates (ES_t) and term premiums (TP_t).

We modify the regression from Equation 2 to account for the new dependent variables:

$$\begin{aligned} \Delta ES_t^n &= \beta_0 + \beta_{HF}\Delta HF_{net,t} + \beta_X' X_t + \varepsilon_t \\ \Delta TP_t^n &= \beta_0 + \beta_{HF}\Delta HF_{net,t} + \beta_X' X_t + \varepsilon_t \end{aligned} \tag{3}$$

The results for these regressions are presented in Table 4. Four panels are presented related to the movements in total yields, expected short rates, term premiums, and term premium levels. The total yield results are very close to our baseline results from earlier, as we would expect. When we look at changes in short rates and term premiums, we see negative coefficients for both, but stronger results for the term premium channel. For example, at the five-year maturity the ES-related coefficient is -2.7 while that for TP is -3.5. Coefficients across maturities in the TP regressions are economically and statistically significant, while the same cannot be said for ES. Note that the sum of β_{HF} across the two equations above equals the coefficient for total yield changes as the dependent variable.

3.1.4 Real Yields and Inflation Compensation

Another dimension of interest is the decomposition of nominal yields into real yields and total inflation compensation (expected inflation and inflation risk premium). As our sample is fully contained in the past decade, we take advantage of yield data on Treasury Inflation Protected Securities (TIPS) to examine whether hedge fund demand is implicitly associated with real yields or inflation compensation. More precisely we modify our baseline regression to account for new dependent variables:

$$\begin{aligned} \Delta TIPS_t^n &= \beta_0 + \beta_{HF}\Delta HF_{net,t} + \beta_X' X_t + \varepsilon_t \\ \Delta\left(y_t^n - TIPS_t^n\right) &= \beta_0 + \beta_{HF}\Delta HF_{net,t} + \beta_X' X_t + \varepsilon_t \end{aligned} \tag{4}$$

where $TIPS_t^n$ is the real yield on a bond with maturity n.

Results for these regressions are presented in Table 5. As $TIPS$ primarily trade at longer maturities, we present results for maturities 5Y and above. Within each panel, the first column represents results for the baseline result from earlier, while the following two columns relate to coefficients from the above equations. It is clear that the coefficient on TIPS is larger and more significant at lower maturities, as it decreases in absolute value from -3.49 basis points at the five-year horizon to -1.33 b.p. at the longer end. As a percentage of the total baseline coefficient, as well, it decreases from 56.4% to 29.8%. An alternative interpretation of this result is that movements in hedge fund demand are more greatly associated with the (total) inflation compensation in bond yields, as maturity increases.

3.2 Robustness

In an ideal world, our baseline measure would reflect an independent or orthogonal movement in hedge fund demand. However, there are a few other factors we haven't directly accounted for. Namely, there are other players who exhibit demand for U.S. Treasuries, such as primary dealers and foreign investors. Furthermore, as our dependent variables are bond yields, it is important to simultaneously account for U.S. monetary policy actions. If hedge funds are responding to Federal Reserve actions, we might be masking an underlying driver of yields. In this subsection we show that results are robust to controlling for these effects.

3.2.1 Other Sources of Demand in Treasury Markets

By construction, primary dealers play an important role in the market making of Treasury securities. Often they purchase securities in primary markets (Treasury auctions) to later sell them off to other investors such as hedge funds, insurance companies, pension funds, and other financial institutions. In some cases, they also hold on to Treasuries to keep active inventory. Due to their important role, we control primary dealer activity in Treasury markets using data from the Federal Reserve Bank of New York. We focus on two variables of interest – (1) the change in primary dealer net holdings and (2) primary dealer volume. The first variable accounts for dealer demand while the second imprecisely measures the aggregate market demand for Treasuries, assuming that a large majority of transactions are routed through these dealers.[8]

In Table 7 we modify the baseline regression specification to include the above two variables:

$$\begin{aligned}\Delta y_t^m &= \beta_0 + \beta_{HF}\Delta HF_{net,t} + \Delta PrimHold_t + \beta_X' X_t + \varepsilon_t \\ \Delta y_t^m &= \beta_0 + \beta_{HF}\Delta HF_{net,t} + PrimVol_t + \beta_X' X_t + \varepsilon_t\end{aligned} \tag{5}$$

As the primary dealer holdings variable is a level variable we take its monthly change while the primary dealer volume variable is treated as a flow, both at the end of the month. The change in primary holdings is additionally scaled by the 5Y bond return, similar to the hedge fund exposures. In the table we show that while dealer holdings (and their flows) matter for bond yields, they do not fully attenuate the effects of hedge funds. In the case of the 5Y Treasury yields for example (see middle panel), we show that the inclusion of primary holdings reduces the absolute coefficient from 6.2 to 4.5 b.p. This latter number is still statistically significant. We also find that dealer volume is relatively insignificant and becomes even weaker as we move to longer durations in the term structure. Moreover, as shown in Column 6 of the Table, hedge fund position movements continue to play an important role for bond yields, as we control for primary dealer effects.

A second control we focus on is the foreign investor market for Treasuries. Using the Major Foreign Holders table from the Treasury International Capital (TIC) database, we are able to construct a monthly time series that accounts for both foreign official holdings (e.g., central banks) as well as foreign investors more broadly (e.g. sovereign wealth funds). After constructing a series of levels, we again first difference this series and divided by the 5Y return on Treasuries. The specification here is similar to the one in the baseline results except we include the change in foreign holdings. The results of this regression are provided in Table 6. We show in the table that again, while movements in foreign holdings significantly impact yields, they do not dramatically attenuate the role of hedge funds. In the case of the 5Y yields, the coefficient attenuates from 6.2 to 5.1 b.p. Meanwhile foreign holdings seem to

[8] When computing these variables we only account for data entries related to coupon bonds. We include all maturities in our aggregate measure. See https://www.newyorkfed.org/markets/counterparties/primary-dealers-statistics for more details.

display a 7.0 b.p. effect on yields in the joint specification.

3.2.2 Controlling for US Monetary Policy

As central banks influence the term structure of interest rates, in some cases the longer end of the yield curve using large scale asset purchases and quantitative easing, it is important to simultaneously account for monetary policy when measuring Treasury market impact. Because our left hand side variable is already the change in yields over a month, we need to use a differently identified variable to account for policy shifts. As monetary policy can be measured in multiple ways, we show that the yield curve is robustly sensitive to hedge fund Treasury demand, while controlling for *two* different policy variables.

The first policy variable is based on high-frequency movements of the 2-year, on-the run Treasury yield, in a 30-minute window surrounding the FOMC announcement. Going back to work by Kuttner (2001), Bernanke and Kuttner (2005), and Gurkaynak, Sack, and Swanson (2005), high-frequency movements of interest rates surrounding FOMC announcements help in the identification of an unexpected monetary policy surprise. In some cases, the surprising nature of the high-frequency change might even be in the opposite direction of the target rate shift altogether. Furthermore, our use of the 2 year maturity is advantageous as it fluctuates in both the conventional and zero lower bound periods (e.g., Hanson and Stein (2015)).

For robustness sake, the second policy variable we examine focuses on the monetary policy shock developed by Bu, Rogers, and Wu (2021). This shock uses the entire term structure of the zero-coupon Treasury yield curve (1 – 30Y) to identify shocks via a Fama-Macbeth type procedure. Because securities from the longer end are used, it appropriately accounts for movements in interest rates due to large-scale asset purchases. To aggregate both of these FOMC day shocks to a monthly frequency, we sum all shocks that occur in a month. For all months where FOMC announcements or significant news do not occur, we set shock values to 0.[9]

In Table 8 we display results while including the monetary policy shocks. In the first two columns we display the baseline specification and a regression including the 2Y shock term ("Onrun2"), respectively. The following two columns do the same, using the Bu et al. (2021) shock ("BRW"), while limiting the sample to its availability. As our BRW data series ends in December 2019, there are 12 fewer months compared to the full sample. We see across all three yield maturities, top to bottom, monthly yield changes load significantly on 2Y monetary policy-related interest rate movements. Above and beyond these policy-related effects, movements in hedge fund Treasury exposures continue to matter significantly for

[9] This procedure of aggregating high frequency shocks to a lower frequency is common in the literature (e.g., Ottonello and Winberry (2020)).

bond yields. In column 2, many of these coefficients in fact jump in absolute size. Similar results hold in column 4 when we control for the BRW shock.

3.3 Fund Heterogeneity and Market Impact

The next part of our Treasury analysis zeroes in on bond market price sensitivity, based on fund-level heterogeneity. While the time series length of the SEC Form-PF data is relatively short, we have a wide cross-section of funds characterized by multiple dimensions. For this study, we focus on two popular dimensions – fund-specific strategy and balance sheet leverage, to understand whether differently grouped funds have different relationships with financial market prices. We realize that there are several cross-sectional dimensions that would be interesting to look at given the characteristics available in the Form-PF dataset. However, the motivation for examining these two dimensions, partly stems from behavior in the March 2020 episode, where highly-levered, relative value funds were thought to account for large Treasury movements before Federal Reserve actions. Moreover, in this subsection, we look at full sample market impact across fund groups, while in the next one (3.4) we contextualize March 2020 relative to other periods with notable Treasury exposure movements.

3.3.1 Impact by Strategy

Using the Form-PF data, we can classify funds by strategy based on their self-reported strategy-specific data.[10] In Figure 3, we look at the top 5 strategies based on their long exposure to US Treasuries, as a percentage of total long exposure across all hedge funds. On average, multi-strategy and relative value funds tend to be those with the largest Treasury exposures at roughly 32 and 26% of the entire universe, respectively. This is followed by macro (17.9%), managed futures (4.3%), and equity funds (2.4%). We exclude strategy categories with smaller exposures as their sensitivities are unlikely to contribute to the overall hedge-fund activity.

Based on the strategy-level decompositions of long and short exposures, we run the following regression:

$$\Delta y_t^{5Y} = \beta_0 + \beta_{HF,s} \Delta HF_{net,t}^s + \beta_X' X_t + \varepsilon_t \tag{6}$$

where $\Delta HF_{net,t}^s$ reflects the net growth for strategy s, which is one of the top 5 categories

[10]One of the questions on the Form asks that funds self-report the percentage of NAV going towards a strategy (equity, macro, relative value, event driven, credit, managed futures, or fund of funds). We classify a fund as targeting one of these strategies if that strategy meets a 75% threshold. If no strategy satisfies this, we classify it as a multi-strategy fund.

presented above. Note that the sum of exposure changes across all strategies, $\sum_s \Delta HF^s_{net,t} = \Delta HF_{net,t}$, the variable used in most of our tests from earlier.

Table 9 displays the results for these regressions where control variables are excluded for brevity's sake. Besides equity-focused funds, all other major types of funds display negative sensitivities as we would expect. In particular, multi-strategy and managed futures funds display statistically significant effects. By contrast, the estimated coefficients on changes in exposures for relative value funds are insignificantly negative despite the role they may have played in the March 2020 disruptions in the US Treasury market. One potential reason for this is regarding the types of trades that relative value funds might engage in. Assuming that these funds are heavy Treasury basis traders, movements in their net exposures would be relatively insignificant. The reason is, that movements in long positions (cash Treasury bonds) would be offset by movements in short positions (futures). Hence their net trading behavior would be less dynamic, and its effects would be relatively diminished.

3.3.2 Impact by Leverage Type

Our second characteristic-based test focuses on a popular indicator of firm or institutional risk – balance sheet leverage. As SEC Form-PF provides data on the market value of gross assets *and* net assets we compute a classical leverage measure – the ratio of gross to net assets. The higher this value is for a given fund, one could make the argument that that fund poses a larger risk of influencing market prices, conditional on selling off assets. Put simply, as per this logic, higher leverage funds should have a larger absolute β_{HF}.

Gross and net asset data are quarterly within the Form-PF dataset, so to build our "high leverage" Treasury exposure series we use a sorting algorithm similar to what is used in portfolio construction. Using the latest value of leverage *strictly prior to* time t, we bucket firms into deciles of leverage. Funds in the top 20% are deemed high leverage funds, while the remaining 80% are deemed low leverage funds. After doing so, we build our long, short, and net level series based on the funds in each respective group (low and high leverage). The first difference in the net series (scaled by the return on the 5Y bond) becomes our data of interest. We run three regressions:

$$\begin{aligned}
\Delta y^m_t &= \beta_0 + \beta_{HF,L}\Delta HF^L_{net,t} + \beta'_X X_t + \varepsilon_t \\
\Delta y^m_t &= \beta_0 + \beta_{HF,H}\Delta HF^H_{net,t} + \beta'_X X_t + \varepsilon_t \\
\\
\Delta y^m_t &= \beta_0 + \sum_{i\in\{L,H\}} \beta_{HF,i}\Delta HF^i_{net,t} + \beta'_X X_t + \varepsilon_t
\end{aligned} \tag{7}$$

Table 10 displays the results for these regressions. In the table's top panel, we focus on results with the high leverage group defined as the top 20% of ex-ante leverage. The bottom panel performs robustness with the cutoff defined as the top 10%. We find across both panels that high leverage types seem to have a negligible, statistically insignificant impact on bond yields. For example, at the 5-year maturity, movements in exposures of relatively leverage funds have a -5.7 to -5.8 b.p. association with contemporaneous bond yields. In contrast, the high leverage funds only have a -1.7 to -2.3 b.p. impact. Similar results hold at the 2Y and 10Y maturities.

Why didn't the original logic hold? One possibility is that there is clear self-selection taking place. The high leverage hedge funds (such as relative value and macro funds) take on safer, less dynamic strategies that do not impact market conditions. Meanwhile the low leverage types (such as risk parity, short volatility, and momentum funds) take on less leverage because they place outright, exposed bets on various assets. As a result, their strategies are more responsive to market conditions and their exposures might be more strongly correlated with market prices. A related point is made in Barth et al. (2020) where hedge fund leverage is shown to display a negative relationship with return market betas and return volatilities. While the focus in the former is on examining return risk versus balance sheet characteristics, we more directly examine hedge funds role towards market prices. The two, however, are related.

3.4 March 2020 in Context

In March 2020, riskier asset classes such as credit, commodity, and equity markets all experienced tremendous declines. More surprisingly, the U.S. Treasury market also found itself in a volatile, downward trajectory in early March, before policy announcements in mid-to-late March.[11] Many recent papers suggest that a reduction in basis trading by relative value funds is a key reason behind the Treasury sell-off (e.g., Schrimpf et al. (2020), Barth and Kahn (2021)). In an ideal world we would have intra-month data to examine the proportionate response of daily (or higher frequency) bond yields to negative movements in hedge fund Treasury exposures. But, unfortunately, the Form-PF data is monthly and doesn't allow us to perform such an analysis. That being said, we can still discuss how March 2020 factors into our price impact analysis.

We start by examining major events in Treasury markets where funds increase or decrease their net positions in a large manner. After sorting months based on their absolute change in

[11] While the early part of 2020 featured a downwards movement in interest rates, rates climbed over the first few weeks of March. For example, the 5 year yield jumped from 46 b.p. on March 9 to 79 b.p. on March 18.

net exposures, scaled by that month's 5-year Treasury gross returns, we focus our attention on the top 15 months. Table 11 provides a list of these top months. In the third column from the right, we provide the total change. For example, the top month turns out to be December 2013, when hedge funds posted a \$106 billion reduction in net UST exposures. In the same Table, we also list the percentage contribution of each strategy towards this total. For example, the interpretation of the Multi-Strategy column would be that $63.93\% \times \$106.1 = \$67.8$ billion of the total reduction in exposures was due to this class of funds.

Naturally, we would expect March 2020 to make this list, and indeed it does. It turns out to be the *eleventh* largest month, with a \$70.1 billion reduction in scaled, net exposures. While this is surprising compared to the steep drop in position levels observed in Figure 1, it is reasonable considering that both long and short positions dropped simultaneously in that month. Further, as net (and not long or short) positions that are consistently and robustly associated with bond yield movements, the exposure reductions in March 2020 might be less important than it initially seems, for the sake of price impact. A second observation from the same Table focuses on the absolute role of Multi-Strategy hedge funds. We see across all 15 events the sizable role that this hedge fund group plays. There are many months where they account for a large proportion of total movements (> 75%) and are the largest driver of aggregate exposure changes. Particularly in March of 2020, in which relative value hedge funds had extreme reductions in their positions (109.3% of the total), multi-strategy hedge funds displayed the exact opposite effect at a larger rate (-113.0% of total). To that end, Multi-Strategy funds displayed a more common "flight-to-safety" type behavior that we would expect in a crisis episode.

Beyond this basic analysis of strategy-specific Treasury market demand, we examine how March 2020 might have influenced our price impact estimates. In Figure 4 we present scatter plots, by strategy, of changes in scaled net exposures against movements in the 5 year yield. Only the top 15 months are plotted and the slopes of the fitted, dashed lines represent crude estimates of market impact by strategy. Note that in each plot, all net exposure movements are scaled by the overall volatility of that strategy's exposure movements. If our story held perfectly across all strategies, it would be the case that all points would either lie in the top-left or bottom-right quadrants. Why? Negative movements in net exposures would be associated with depressed bond prices and positive movements in yields. Meanwhile positive movements would be associated with the opposite.

Overall, these four graphs are consistent with this story. In particular, all 15 months line up perfectly in these two quadrants for Multi-Strategy funds. For Managed Futures, 14 of 15 months also line up. Meanwhile, Macro and Relative Value funds each have at least three months that do not align. Most importantly, March 2020 (identified by red labeling) seems to be an outlier weakening price impact estimates. Particularly in the case of Relative Value, we see that March 2020 served as a roughly -5 standard deviation event, despite yields diminishing. Only Multi-Strategy funds displayed the "right" sign on its March 2020 behavior. In Figure 5, we examine whether removing the monetary policy component of yield changes helps these figures. We show that, indeed the outlier effect of March 2020 is attenuated (see Figure (b), for example); however, the effect is not fully corrected.

In summary, the evidence we explore suggests that March 2020, while an extreme movement in long and short UST positions, was not a historically large movement in *net positions* or net demand. That being said, it plays a significant role in biasing the measurement of price impact, particularly for Relative Value and Macro funds. Meanwhile, Multi-Strategy funds display behavior that is time-invariant and dominant towards the identification of the overall price effect.

4 Hedge Fund Exposures as a Risk Factor

Standard asset-pricing theory (e.g., Ljungqvist and Sargent (2012), Cochrane (2005)) predicts that state variables that are procyclical or represent "good states of the world" should carry a positive risk premium in equilibrium. When the asset returns are more exposed to these states (i.e., have higher betas), investors should be compensated to hold them as they do not serve as a hedge to aggregate risk. In this section, we investigate the idea that hedge fund Treasury demand serves as such a priced risk factor in the cross section of Treasury assets. This economic rationale comes from the hypothesis that fluctuations in hedge fund exposures capture the overall industry's ability and willingness to trade in the Treasury market.

The idea that hedge funds or more broadly, financial intermediary characteristics might matter for asset prices is not a new one. He and Krishnamurthy (2013) discusses the idea that financial intermediary constraints are theoretically a driving force behind the pricing of institutionally-held assets, such as mortgage-based securities. Two recent papers empirically test these conceptual ideas, using broker dealers' balance sheet information. First, Adrian et al. (2014) show that shocks to the leverage of broker-dealers are priced in a large number of cross-sectional portfolios. Similarly, He et al. (2017) show that shocks to the equity capital ratio of financial intermediaries (mainly primary dealers) are priced in a number of risky asset classes including Treasuries, equities, corporate and sovereign bonds, and currencies.[12] Finally, a recent paper by Du, Hebert, and Li (2022) suggests that constrained dealer activity

[12] Interestingly, both of these papers draw significant yet contradictory results using datasets that are inherently linked.

in U.S. Treasury markets can be linked to the slope of the yield curve. We show that due to the time series length of our data, we unfortunately won't be able to draw as precise conclusions as these authors do. However, the hedge fund exposure data provide a fresh and unique perspective that is highly connected to these earlier ideas. As many of these dealers and prime brokers directly interact with hedge funds, the parallels are natural.

4.1 Model Overview

We investigate a standard cross-sectional asset pricing model (e.g., Ross (1976)), where we measure risk compensation for the key hedge fund factor from earlier, $\Delta HF_{net,t}$. The model we estimate will be of the form:

$$\mathbb{E}\left[R_{it} - R_{ft}\right] = \beta^{i}_{HF}\lambda_{HF} + \beta^{i\prime}_{X}\lambda_{X} \tag{8}$$

In the above equation, the left-hand side variable represents the excess return on an asset i, β^{i}_{HF} is the exposure of asset i's excess returns to movements in hedge fund Treasury holdings, and λ_{HF} is the risk compensation for each additional unit of β. Similar statements hold for β_X and λ_X. Note that the estimate of λ_{HF} will be different from $\mathbb{E}\left[\Delta HF_{net,t}\right]$ as it is not a tradable factor (see Cochrane (2005) for a larger discussion).

If high levels of hedge fund net exposure growth are truly a positive state of the world, with lower marginal utilities for intermediaries, then we would expect that assets that load on it at a higher rate (a higher β^{i}_{HF}) would yield higher expected returns. Put differently, our hypothesis is that $\lambda_{HF} > 0$. Following the results from the bond yield regressions earlier, we also test two alternative factors in addition to hedge fund exposures – real industrial production growth and inflation.

Estimation Details

To estimate the key parameters, we take advantage of the full cross-section of the Gurkaynak et al. (2007) dataset. As there are 30 maturities of zero-coupon bond data available (1Y – 30Y), we compute the one-month holding period return of purchasing an n-period bond at time t and selling it off as an $n-1$ period bond at $t+1$. Such a procedure is repeated across all 30 maturities at each point in time.[13] Through this procedure we build a panel of 30 returns from January 2013 through December of 2020. To compute excess returns we use the 1-month Treasury bill rate from the St. Louis Federal Reserve Economic Data (FRED).

[13] As a simple example, for the 5Y bond, we compute a return assuming that an investor purchases it as a 60-month bond and sells it off as a 59 month bond the following period. In order to derive the zero coupon bond yield on the 59 month bond, we linearly interpolate across the yield curve at that point in time.

Following Hansen and Singleton (1982) and Cochrane (2005), we use the generalized method of moments (GMM) to jointly estimate the following $\hat{\Theta}$ in one step:

$$\hat{\Theta} = \left\{ \hat{\beta}^{1Y}, \hat{\beta}^{2Y}, \ldots, \hat{\beta}^{30Y}, \hat{\lambda}_{HF}, \hat{\lambda}_{X} \right\}$$

Performing the joint estimation allows us to avoid the errors-in-variables problem that arises from estimating parameters using the Fama-Macbeth two step procedure. More specifically, our GMM criterion function is of the form:

$$g_T \left(X | \Theta \right)' W g_T \left(X | \Theta \right)$$

where $g_T \left(\ldots \right) \equiv \frac{1}{T} \sum_{t=1}^{T} g \left(x_t | \Theta \right)$ and x_t indicates all relevant bond return and factor data at a point in time. In terms of moment conditions, the following restrictions are used *per maturity*:

$$\mathbb{E} \begin{pmatrix} R_{it} - R_{ft} - \left(\beta_0^i + \beta_{HF}^i \Delta HF_{net,t} + \beta_X^{i'} X_t \right) \\ \left(R_{it} - R_{ft} - \left(\beta_0^i + \beta_{HF}^i \Delta HF_{net,t} + \beta_X^{i'} X_t \right) \right) \times \Delta HF_{net,t} \\ \left(R_{it} - R_{ft} - \left(\beta_0^i + \beta_{HF}^i \Delta HF_{net,t} + \beta_X^{i'} X_t \right) \right) \otimes X_t \\ R_{it} - R_{ft} - \left(\lambda_0 + \beta_{HF}^i \lambda_{HF} + \beta_\pi^i \lambda_\pi \right) \end{pmatrix} = \begin{pmatrix} \vdots \\ 0 \\ \vdots \end{pmatrix}$$

Hence $g(x_t|\Theta)$ will be a stacked set of these moments. For sake of simplicity, we set W as the identity matrix and allow for heteroskedasticty and autocorrelation when estimating the covariance matrix of $g \left(x_t | \Theta \right)$.[14]

4.2 Results

In Table 12, we present results related to our baseline estimation. There are four models we separately estimate: (1) a single factor model with industrial production growth, (2) a model with inflation, (3) a model with movements in hedge fund Treasury exposures, and (4) a joint model of inflation and the hedge fund factor. In Model 1, we show that economic growth is barely priced in the nominal term structure over this period, as β's and λ are jointly insignificant. Meanwhile, Models 2 and 3 show that inflation and hedge fund β's are significant and increasing across the board. Finally, in Model 4, we show that both factor β's are significant in the joint specification. While the return exposures are significant, the average prices of risk are not. The inflation price of risk, λ_π, is negative but insignificant in

[14] In an ideal world one could use the two-step or iterative step estimation algorithm. Due to issues inverting the resulting spectral density matrix from an iterative algorithm, we use the identity weight matrix. We also confirm that our estimates are of similar sign and magnitude as those that arise from a Fama-Macbeth type procedure.

Models 2 and 4. A similar story holds for the hedge fund price of risk.

It is worth mentioning that signs on parameters related to the two key factors (inflation and hedge fund Treasury demand) are economically intuitive. Hedge fund betas are positive, as movements in Treasury demand increase prices and holding period returns. Similarly, λ_{HF}, while insignificant, does maintain a positive point estimate as hypothesized earlier. Analogous statements can be drawn for inflation in the opposite direction. Because high inflation is a negative state of the world, nominal bonds are negatively exposed to it ($\beta^i_\pi < 0$) and bonds that pay out in those states (i.e. with higher betas) act as a hedge ($\hat{\lambda}_\pi < 0$).

While the estimates of λ are imprecise, the cross-sectional fit of the model is a different story. In the top two panels of Figure 6, we plot cross-sectional betas of returns concerning inflation and hedge fund Treasury exposures against expected excess returns. The slopes of the fitted lines in both diagrams correspond roughly to the λ estimates. While the standard errors of these λ estimates are imprecise, it is clear from these figures that there is a stark visual relationship between hedge fund Treasury beta and average expected returns. In the bottom panel, we show the overall fit of the model (expected returns in the data vs. fitted returns of the model). The fitted line is very close to a 45-degree line here.

4.3 Role of Sample Size

While we try to help the identification of the λ_{HF} through a broad set of cross-sectional assets, it turns out that the restrictive monthly time series (only 95 months in total) plays a key role in the imprecise estimates. In this subsection we argue that the imprecise estimates of the price of risk are partially due to the time series length. One key variable that we would expect to be priced unequivocally is inflation. Both statistically and in terms of economic intuition, many studies have shown a significant inflation risk premium component embedded in the nominal yield curve (see Bansal and Shaliastovich (2013)). The fact that it does not show up as a priced risk factor is puzzling here. While we cannot extend the hedge fund dataset back further we can look at the role of inflation if we were to extend it to a longer bond return dataset going back.

Using Fama US Treasury bond portfolios available through Wharton Research Data Services (WRDS) we extend our analysis going back to January 1952. While the cross-section is not as large with a maximum of 12 Treasury portfolios, the time series length ends up helping substantially. In Table 13, we display results from the historical pricing of a one factor model (PCE inflation). Similar to our results earlier in Table 12, the β estimates are all negative and significant. What is different, however, is the significance of λ_π. Inflation carries a negative risk premium in Treasury returns, and the length of the time series matters greatly. For robustness, we cut the sample in two ways, (1) capturing the full cross section of 12 securities (going back to February 1959) and (2) only capturing a cross section of 11 securities (going back to January 1952). Results are qualitatively consistent across both setups.

While we cannot say with one hundred percent certainty that risks related to hedge fund Treasury demand are an aggregate risk factor carrying a significant, positive risk premium, we can say that the sample size contributes to the estimate's imprecision. In this exercise we extend the time series length and focus on inflation to show that even a variable of great importance in Treasury markets suffers the same statistical issues when it faces a short time series.

4.4 Price of Risk by Strategy and Leverage Type

Analogous to earlier tests involving fund heterogeneity and bond yields, we investigate the risk compensation of hedge fund Treasury exposures by fund grouping. We start by estimating separate, two-factor models incorporating both inflation and movements in net hedge fund exposures by strategy:

$$\mathbb{E}\left[R_{it} - R_{ft}\right] = \beta^{i}_{HF,s}\lambda_{HF,s} + \beta^{i'}_{\pi}\lambda_{\pi} \tag{9}$$

where $\lambda_{HF,s}$ indicates the risk premium for a particular strategy s. The results to these strategy-specific estimations are provided in Table 14. We do not display inflation-related estimates for brevity. Our results suggest that only two strategies display positive beta's and λ's with respect to that strategy's net Treasury exposure movements – multi-strategy and managed futures. These results are in line with the yield regression results where hedge fund demand only mattered for prices so far as it arose from multi-strategy and managed futures funds.

The last specification of the model jointly takes into account inflation and net exposure movements from low leverage and high leverage hedge funds, separately. Hence, in total three variables are tested as risk factors. In Table 15, we display these results and conclude that movements in net exposures of low leverage funds are responsible for the positive λ that is attributable to overall movements in hedge fund exposures. Only inflation and the low leverage factor display significant beta's as well. These results align with the regression evidence from earlier, where we use changes in bond yields as the dependent variable.

5 Conclusion

To shed light on how hedge funds might affect prices and possibly amplify underlying shocks, we estimate the monthly market impact of changes in net hedge fund exposures on U.S. Treasury yields. The association between yields and hedge fund demand is economically and statistically significant, and is robust to several potential mitigating factors, including reverse causality, the activity of other prominent players in Treasury markets, and monetary policy. We also find interesting results in the cross section when we examine hedge funds by strategy or leverage type. Furthermore, March 2020, which does not display a historically large reduction in net exposures, does seem to serve as an outlier that biases the absolute magnitude of price impact estimates.

Overall, these findings indicate that the trading activities of hedge funds can be linked to market price movements. At the same time, it is important to recognize that these findings do not show that hedge funds are the sole or decisive driver of price fluctuations in the Treasury market. Neither are they necessarily the source or originator of fundamental shocks that cascade through the financial system. Clearly, there are other forces that drive price movements in those markets. Extrapolating from this last point, it might be difficult to demonstrate that hedge fund trading during the March 2020 episode was the principal force behind the large fluctuations in Treasury yields and the decrease in liquidity. However, they might have served the role of an amplification mechanism.

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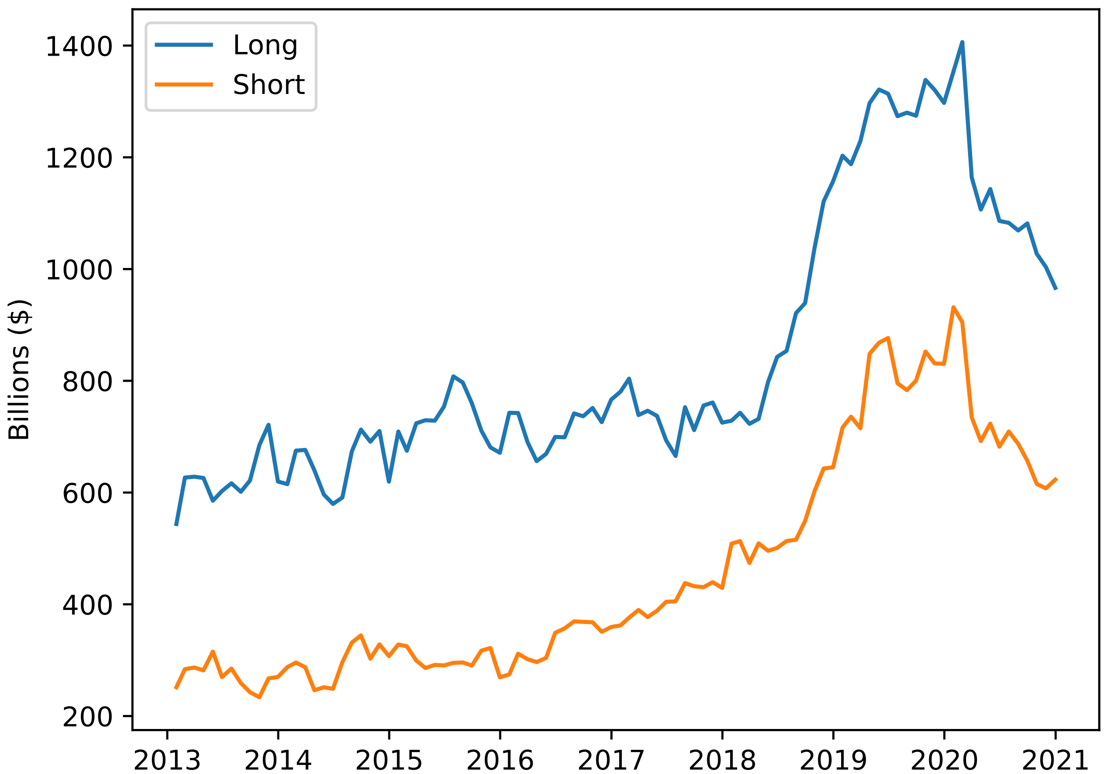
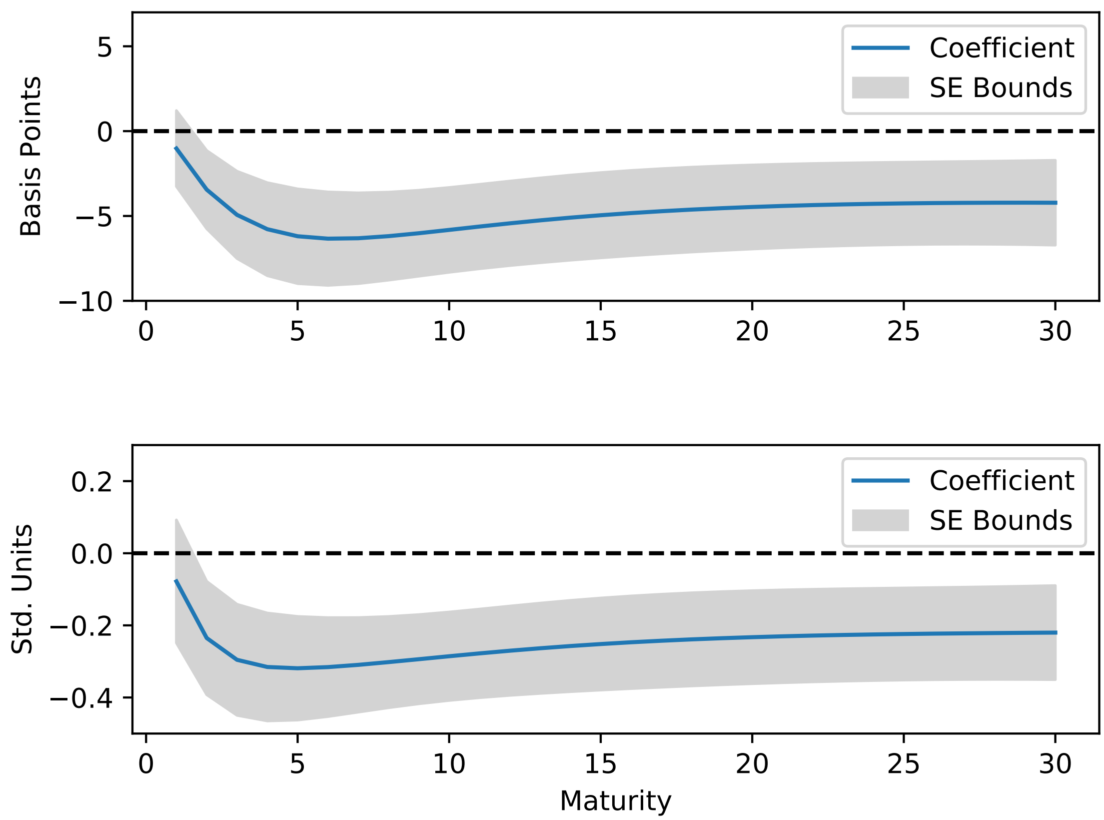
Figure 1: **Hedge Fund Exposures to US Treasuries**



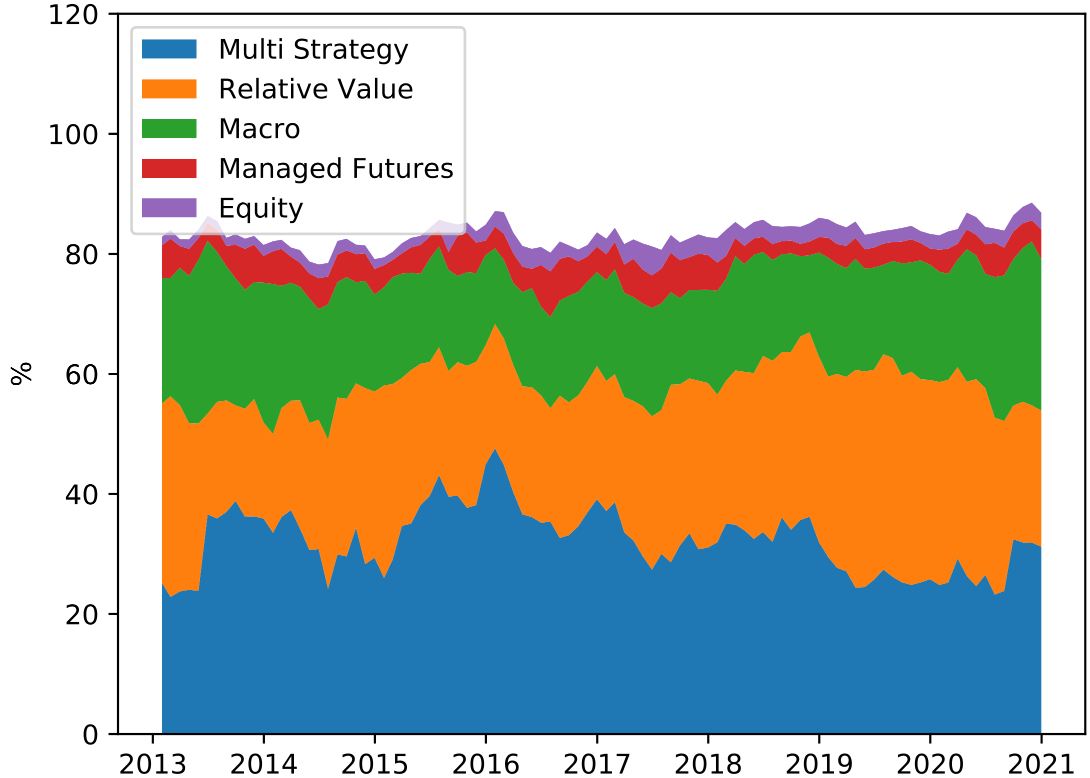
This figure displays monthly, aggregate long and short exposures to US Treasury securities from January 2013 through September 2020 for qualifying hedge funds in the Form-PF universe. Exposures include outright holdings of Treasury securities and derivative contract holdings (eg. futures).

Figure 2: **Sensitivities to HF Exposures, Across Maturities**



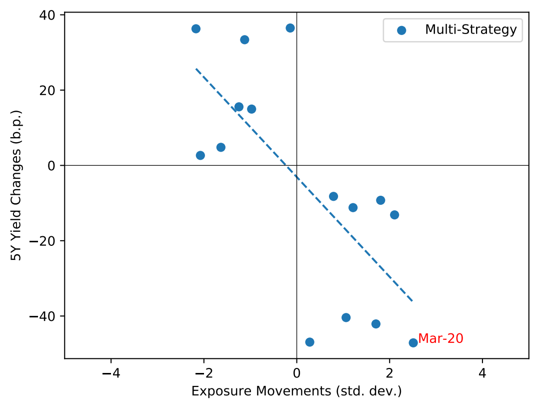
This figure describes the results from projecting bond yield changes onto the (adjusted) net growth in HF exposures, across various maturities. The top panel states sensitivities in basis point terms while the bottom panel in standardized terms. All regressions include controls from the main text and the solid blue line provides the coefficient of interest. The grey band reflects the 95% standard error band surrounding the estimates. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Figure 3: **Long Treasury Exposures by HF Strategy Type**

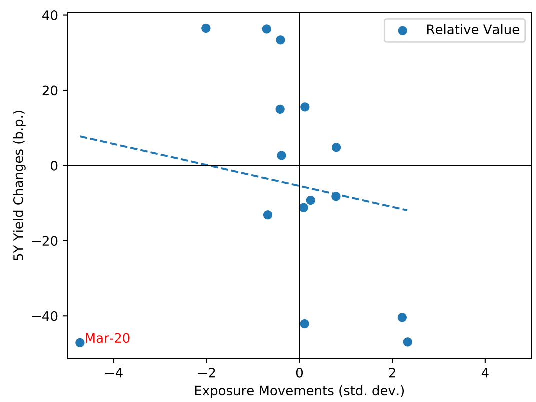


This figure displays the percentage of total HF long exposures by fund strategy type. The top 5 strategies, by average long exposure percentages, are displayed. See text for more details.

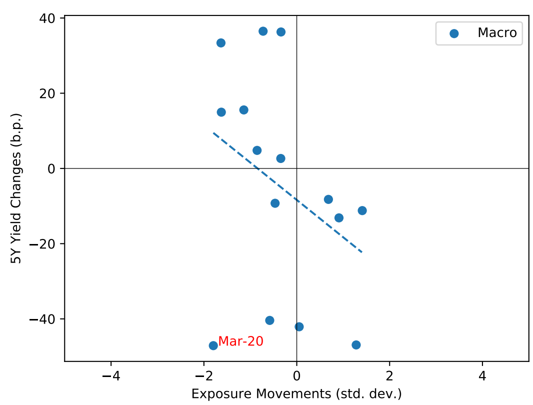
Figure 4: **Exposure Movements vs. Yields Across Notable Events**



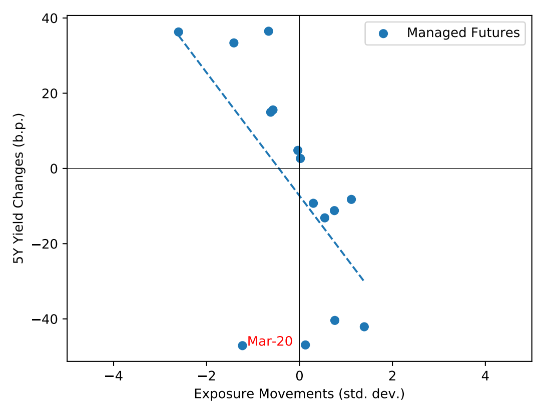
(a) Multi-Strategy Funds



(b) Relative Value Funds



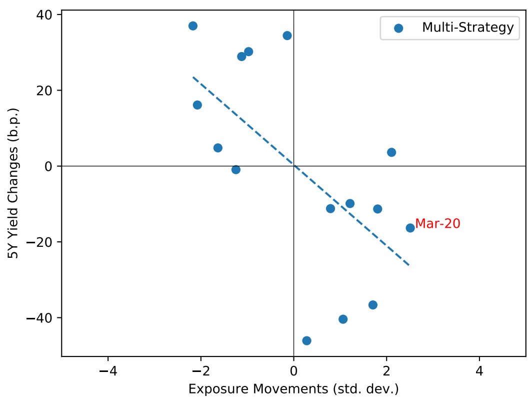
(c) Macro Funds



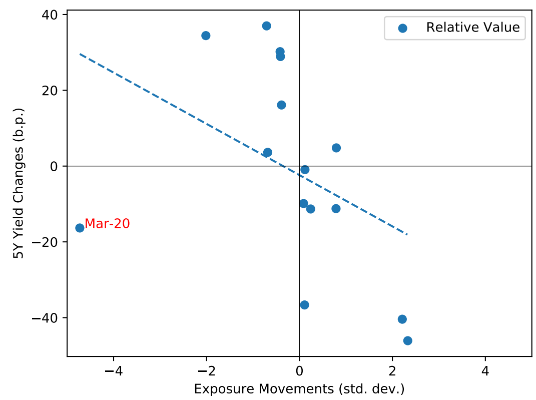
(d) Managed Futures Funds

This figure displays scatter plots of strategy-level exposure movements against corresponding movements in monthly yields. A total of 15 points are displayed, which correspond to months with large absolute changes in net exposures. The precise months are listed in Table 11. Yield changes are in basis points while exposure movements are demeaned and scaled by full sample, strategy-level means and standard deviations. The data point corresponding to March 2020 is specifically marked.

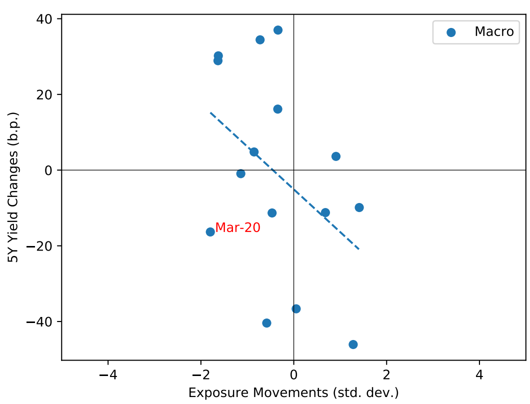
Figure 5: **Exposure Movements vs. Yields, Controlling for Monetary Policy**



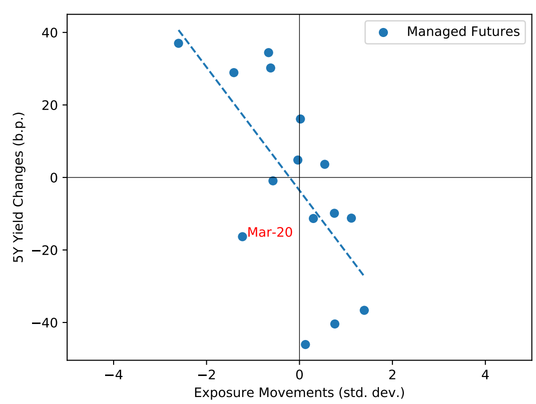
(a) Multi-Strategy Funds



(b) Relative Value Funds



(c) Macro Funds



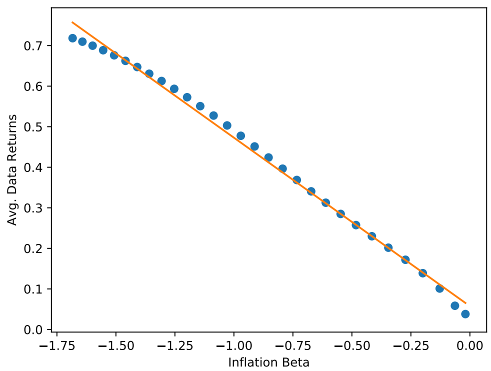
(d) Managed Futures Funds

This figure displays scatter plots of strategy-level exposure movements against corresponding movements in monthly yields that are corrected for monetary policy movements. A total of 15 points are displayed, which correspond to months with large absolute changes in net exposures. The precise months are listed in Table 11. Yield changes are in basis points and computed as $\Delta y_t^{5Y} - \hat{\beta}_m s_t$, where $\hat{\beta}_m$ is the fitted coefficient from the regression:

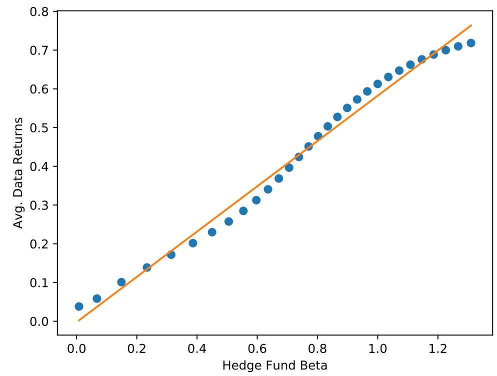
$$\Delta y_t^{5Y} = \beta_0 + \beta_m s_t + \eta_t$$

Here, s_t is the surprise change in the 2Y On-the-Run monetary shock, as described in Section 3.2.2. Meanwhile, exposure movements are demeaned and scaled by full sample, strategy-level means and standard deviations. The data point corresponding to March 2020 is specifically marked.

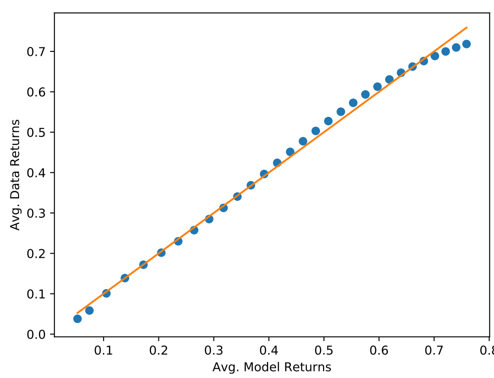
Figure 6: **Factor Betas vs. Treasury Returns**



(a) PCE Inflation



(b) Hedge Fund Treasury Exposures



(c) Data vs. Model $E(R)$

In this Figure, the top two graphs represent scatter plots of estimated beta coefficients against average Treasury returns, based on estimates from a 2-factor asset pricing model including inflation and the net hedge fund UST exposures variable. The bottom graph displays the model's fit against the average returns in the data. See main text for more details.

Table 1: **Summary Statistics**

	Mean	Stdev	25%	75%	Num Periods	Total Num Funds	Avg Num Funds
				Change in Exposures ($, Billions)			
Long	4.45	49.12	-23.45	37.94	95	1523	573.82
Short	3.91	36.20	-11.32	18.55	95	1272	454.24
Net	0.54	40.90	-26.00	30.98	95	1639	627.66
				Change in Net Exposures by Strategy			
Multi-Strategy	0.46	31.46	-19.87	20.81	95	441	160.30
Relative Value	-0.24	16.31	-6.89	8.40	95	220	76.91
Macro	0.02	12.92	-7.70	7.68	95	203	75.15
Managed Futures	0.12	11.03	-7.18	7.11	95	79	30.22
Equity	0.16	5.59	-1.74	2.32	95	323	81.84
Total	0.54	40.90	-26.00	30.98	95	1639	627.66
				Bond Yield Changes (b.p.)			
1Y	-0.08	13.10	-1.97	7.19	96	–	–
3Y	-0.21	16.70	-6.24	11.09	96	–	–
5Y	-0.38	19.42	-10.69	11.55	96	–	–
10Y	-0.92	20.38	-13.31	10.67	96	–	–
15Y	-1.33	19.68	-11.39	11.49	96	–	–
20Y	-1.50	19.20	-10.75	11.03	96	–	–
30Y	-1.32	19.17	-12.23	11.05	96	–	–

This table provides summary statistics of key variables used throughout the paper. The top panel examines the time series properties of aggregated Long, Short, and Net hedge fund exposures to US Treasuries. The right two columns display the total number of funds throughout the sample and average funds per month. The second panel breaks down net exposures by strategy and provides similar statistics. The bottom panel displays summary statistics on the Gurkaynak et al. (2007) bond yield dataset within our time sample of interest, January 2013 through December 2020.

Table 2: **Treasury Market Impact of HF Demand**

	2Y	5Y	10Y	2Y	5Y	10Y	2Y	5Y	10Y
Long Growth	-1.59	-5.19*	-5.29**						
	(2.76)	(2.98)	(2.39)						
Short Growth				1.95	0.29	-0.31			
				(2.17)	(1.80)	(1.60)			
Net Growth							-3.44***	-6.19***	-5.81***
							(1.19)	(1.44)	(1.29)
IndPro	0.33	-1.67	-2.39	0.19	-2.17	-2.91*	0.60	-1.40	-2.18
	(1.33)	(1.76)	(1.79)	(1.10)	(1.42)	(1.60)	(1.45)	(1.77)	(1.78)
InflPCE	3.19***	6.82***	7.96***	2.66***	6.16***	7.40***	2.95**	6.10***	7.24***
	(1.10)	(1.46)	(1.57)	(1.00)	(1.71)	(1.86)	(1.15)	(1.40)	(1.54)
Debt Growth	-0.72	-0.98	-0.92	-0.23	-0.48	-0.53	-0.38	-0.16	-0.12
	(0.92)	(1.46)	(1.58)	(0.81)	(1.18)	(1.34)	(0.94)	(1.45)	(1.47)
R2	0.06	0.14	0.16	0.07	0.08	0.10	0.10	0.18	0.18
N	95	95	95	95	95	95	95	95	95

This table describes the results of the baseline regression of bond yield changes on HF growth variables and controls. Each panel examines a different demand variable; within a panel each column examines a different bond yield. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 3: **Treasury Market Impact of HF Demand, Controlling for Prices**

	2Y	5Y	10Y	2Y	5Y	10Y	2Y	5Y	10Y
					Adjusting Exposures by Treasury Returns				
Long Growth, Adj	-1.64	-5.24*	-5.32**						
	(2.72)	(2.93)	(2.35)						
Short Growth, Adj				1.92	0.28	-0.30			
				(2.15)	(1.79)	(1.60)			
Net Growth, Adj							-3.45***	-6.19***	-5.82***
							(1.18)	(1.42)	(1.27)
R2	0.06	0.15	0.16	0.07	0.08	0.10	0.10	0.18	0.18
N	95	95	95	95	95	95	95	95	95
					Alternative Price Adjustment				
Long Growth, Alt	0.83	-1.99	-2.12						
	(2.69)	(2.79)	(2.13)						
Short Growth, Alt				3.87*	2.84*	2.24*			
				(1.99)	(1.47)	(1.34)			
Net Growth, Alt							-2.37*	-4.68***	-4.32***
							(1.35)	(1.65)	(1.43)
R2	0.05	0.09	0.11	0.11	0.10	0.11	0.08	0.13	0.14
N	95	95	95	95	95	95	95	95	95

This table describes the results from including growth variables adjusted for price movements. The top panel uses an adjustment methodology where hedge fund exposure variables are scaled by gross Treasury returns, while the bottom panel scales the exposure and its lag by price levels. Control variables are included in the regressions but not displayed for brevity. Each sub-panel examines a different demand variable; within a panel, each column examines a different bond yield. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 4: **Risk Premium Decomposition of Treasury Market Impact**

	2Y	5Y	10Y	2Y	5Y	10Y
		Total Yields			*Expected Short Rates*	
Net Growth, Adj	-3.41***	-6.20***	-5.89***	-1.57	-2.72*	-2.73**
	(1.17)	(1.42)	(1.29)	(1.48)	(1.41)	(1.20)
IndPro	0.61	-1.40	-2.23	2.24	1.26	0.75
	(1.45)	(1.77)	(1.80)	(1.80)	(1.60)	(1.34)
InflPCE	2.92**	6.10***	7.32***	1.29	1.86*	1.95**
	(1.14)	(1.39)	(1.57)	(1.35)	(1.12)	(0.94)
Debt Growth	-0.38	-0.16	-0.13	0.23	0.11	0.07
	(0.93)	(1.45)	(1.49)	(1.14)	(1.10)	(0.96)
R2	0.10	0.18	0.18	0.06	0.08	0.09
N	95	95	95	95	95	95
		Term Premiums			*Term Premium (Levels)*	
Net Growth, Adj	-1.83**	-3.47***	-3.16***	1.82	1.91	2.47
	(0.91)	(0.77)	(1.19)	(1.25)	(2.83)	(4.49)
IndPro	-1.62***	-2.66***	-2.99**	-2.95	-4.93	-6.34
	(0.59)	(0.90)	(1.31)	(1.87)	(3.90)	(5.36)
InflPCE	1.63**	4.23***	5.37***	0.08	-2.56	-2.83
	(0.66)	(0.92)	(1.25)	(1.59)	(3.25)	(4.77)
Debt Growth	-0.61	-0.26	-0.20	-9.18***	-20.19***	-27.39***
	(0.43)	(0.82)	(1.11)	(1.49)	(3.30)	(4.69)
R2	0.09	0.17	0.12	0.14	0.14	0.12
N	95	95	95	95	95	95

This table describes the results from decomposing yield changes ("Total Yields") into movements due to those in expected future short rates and term premiums. The decomposed yield data are taken from updated estimates by Adrian et al. (2013). Each panel examines a different component of yield changes; within a panel, each column examines a different maturity. The bottom right panel additionally looks at HF exposure effects on term premium levels. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 5: **Real Yields and Treasury Market Impact**

	5Y Yields			*7Y Yields*		
	Total	TIPS	Residual	Total	TIPS	Residual
Net Growth, Adj	-6.19***	-3.49*	-2.70*	-6.31***	-3.11*	-3.20**
	(1.42)	(1.98)	(1.60)	(1.36)	(1.65)	(1.32)
IndPro	-1.41	-2.59	1.19	-1.91	-2.78	0.87
	(1.77)	(2.38)	(1.27)	(1.83)	(2.05)	(1.02)
InflPCE	6.11***	0.58	5.53***	6.92***	2.17	4.75***
	(1.40)	(2.50)	(2.00)	(1.54)	(2.31)	(1.60)
Debt Growth	-0.16	-4.02	3.86**	-0.11	-3.57*	3.46***
	(1.45)	(2.62)	(1.69)	(1.53)	(2.11)	(1.21)
R2	0.18	0.07	0.18	0.18	0.08	0.19
N	95	95	95	95	95	95
	10Y Yields			*20Y Yields*		
	Total	TIPS	Residual	Total	TIPS	Residual
Net Growth, Adj	-5.82***	-2.29	-3.54***	-4.47***	-1.33	-3.14***
	(1.27)	(1.48)	(1.08)	(1.26)	(1.35)	(0.95)
IndPro	-2.19	-2.39	0.20	-2.75	-1.83	-0.93
	(1.78)	(1.80)	(0.82)	(1.79)	(1.67)	(0.69)
InflPCE	7.24***	2.84	4.41***	7.44***	3.32*	4.12***
	(1.54)	(2.17)	(1.33)	(1.68)	(1.96)	(1.03)
Debt Growth	-0.11	-3.28**	3.17***	0.05	-2.62**	2.68***
	(1.47)	(1.66)	(0.85)	(1.23)	(1.29)	(0.69)
R2	0.18	0.07	0.20	0.16	0.07	0.19
N	95	95	95	95	95	95

This table describes the results from decomposing yield changes ("Total") into movements due to real yields ("TIPS") and compensation for inflation ("Residual"). Real yields are taken from the TIPS yield curve. Each panel examines a different maturity of yield changes. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 6: **Foreign Treasury Demand and HF Price Impact**

	2Y Yields			*5Y Yields*			*10Y Yields*		
	HF	Foreign	Both	HF	Foreign	Both	HF	Foreign	Both
Net Growth, Adj	-3.45***		-2.82**	-6.19***		-5.12***	-5.82***		-4.52***
	(1.18)		(1.22)	(1.42)		(1.72)	(1.27)		(1.60)
ForHold Growth, Adj		-4.61*	-4.14*		-7.88***	-7.04***		-9.33***	-8.58***
		(2.41)	(2.44)		(2.56)	(2.66)		(2.47)	(2.54)
IndPro	0.60	1.87	2.04	-1.41	0.72	1.05	-2.19	0.52	0.80
	(1.45)	(1.65)	(1.91)	(1.77)	(1.93)	(2.33)	(1.78)	(1.97)	(2.26)
InflPCE	2.95***	2.56	2.55*	6.11***	5.44***	5.44***	7.24***	6.43***	6.43***
	(1.14)	(1.56)	(1.50)	(1.40)	(1.99)	(1.73)	(1.54)	(2.08)	(1.84)
Debt Growth	-0.38	0.13	0.23	-0.16	0.69	0.87	-0.11	0.98	1.14
	(0.94)	(0.94)	(1.13)	(1.45)	(1.32)	(1.65)	(1.47)	(1.35)	(1.59)
R2	0.10	0.14	0.18	0.18	0.23	0.29	0.18	0.29	0.34
N	95	95	95	95	95	95	95	95	95

This table describes the results from including growth rates of foreign holdings of US Treasury securities, as given through Treasury International Capital (TIC) data. Each panel examines a different yield maturity. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 7: **The Role of Primary Dealers Towards HF Price Impact**

2Y Yields

	(1)	(2)	(3)	(4)	(5)	(6)
Net Growth, Adj	-3.45***		-2.25**		-3.06**	-2.01*
	(1.18)		(1.07)		(1.24)	(1.05)
PrimHold Growth, Adj		-5.48***	-4.85***			-4.42***
		(0.95)	(1.19)			(1.08)
PrimVol				-4.53*	-4.37*	-3.93*
				(2.47)	(2.64)	(2.29)
R2	0.10	0.17	0.19	0.14	0.18	0.26
N	95	95	95	96	95	95

5Y Yields

	(1)	(2)	(3)	(4)	(5)	(6)
Net Growth, Adj	-6.19***		-4.52***		-6.00***	-4.42***
	(1.42)		(1.30)		(1.50)	(1.30)
PrimHold Growth, Adj		-8.03***	-6.77***			-6.60***
		(1.13)	(1.38)			(1.41)
PrimVol				-2.54	-2.25	-1.59
				(3.17)	(3.35)	(2.87)
R2	0.18	0.23	0.28	0.10	0.19	0.28
N	95	95	95	96	95	95

10Y Yields

	(1)	(2)	(3)	(4)	(5)	(6)
Net Growth, Adj	-5.82***		-4.33***		-5.69***	-4.27***
	(1.27)		(1.26)		(1.40)	(1.29)
PrimHold Growth, Adj		-7.25***	-6.05***			-5.95***
		(1.31)	(1.45)			(1.55)
PrimVol				-1.54	-1.48	-0.89
				(3.39)	(3.52)	(3.16)
R2	0.18	0.21	0.25	0.10	0.18	0.25
N	95	95	95	96	95	95

This table describes the results from including variables related to primary dealer U.S. Treasury demand. Two key variables are used – the growth rate of primary dealer Treasury holdings and monthly volume of primary dealer trading. Control variables are included in the regressions but not displayed for brevity. From top to bottom, each panel examines a different yield maturity. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 8: **Monetary Policy and HF Price Impact**

2Y Yields

	(1)	(2)	(3)	(4)
Net Growth, Adj	-3.45***	-3.95***	-4.93***	-4.79***
	(1.18)	(0.99)	(0.98)	(0.95)
Onrun2		6.35***		
		(1.88)		
BRW				2.56**
				(1.16)
Full Sample	Y	Y	N	N
MP Shock Sample	Y	Y	Y	Y
R2	0.10	0.28	0.17	0.20
N	95	95	83	83

5Y Yields

	(1)	(2)	(3)	(4)
Net Growth, Adj	-6.19***	-6.77***	-8.21***	-8.03***
	(1.42)	(1.24)	(1.11)	(1.13)
Onrun2		7.28***		
		(1.65)		
BRW				3.46*
				(1.81)
Full Sample	Y	Y	N	N
MP Shock Sample	Y	Y	Y	Y
R2	0.18	0.31	0.25	0.29
N	95	95	83	83

10Y Yields

	(1)	(2)	(3)	(4)
Net Growth, Adj	-5.82***	-6.28***	-7.24***	-7.13***
	(1.27)	(1.16)	(1.15)	(1.16)
Onrun2		5.79***		
		(1.48)		
BRW				2.22
				(1.97)
Full Sample	Y	Y	N	N
MP Shock Sample	Y	Y	Y	Y
R2	0.18	0.26	0.22	0.23
N	95	95	83	83

This table describes the results from including variables accounting for monetary policy surprises. Two key variables are tested – the surprise change in the 2Y On-the-Run security surrounding an FOMC announcement ("Onrun2") and the monetary shock constructed in Bu et al. (2021). Control variables are included in the regressions but not displayed for brevity. From top to bottom, each panel examines a different yield maturity. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 9: **Treasury Market Impact of HF Demand, Across Strategy**

	Total	Multi-strategy	Relative Value	Macro	Managed Futures	Equity
Net Growth, Adj	-6.19***	-3.94***	-1.67	-1.07	-10.45***	1.98**
	(1.42)	(1.40)	(2.46)	(2.24)	(1.17)	(0.90)
R2	0.18	0.12	0.08	0.08	0.36	0.09
N	95	95	95	95	95	95

This table describes the regression results when breaking out the exposures by strategy type and focusing on the response of 5Y bond yields. Control variables are included in the regressions but not displayed for brevity. Each column examines a different strategy type based on exposure growth within funds associated with that strategy. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 10: **Treasury Market Impact of HF Demand, by HF Leverage**

High Leverage as Top 20%

	2Y				5Y				10Y			
Net Growth, Total	-3.20***				-5.88***				-5.62***			
	(1.19)				(1.48)				(1.29)			
Net Growth, Low Lev		-4.27***		-4.27**		-5.85***		-5.77***		-4.62***		-4.52***
		(1.62)		(1.69)		(1.55)		(1.58)		(1.40)		(1.42)
Net Growth, High Lev			-0.22	-0.08			-2.53	-2.34			-3.44	-3.29
			(2.63)	(2.48)			(2.87)	(2.62)			(2.66)	(2.51)
R2	0.10	0.13	0.05	0.13	0.17	0.17	0.09	0.18	0.17	0.15	0.12	0.17
N	95	95	95	95	95	95	95	95	95	95	95	95

High Leverage as Top 10%

	2Y				5Y				10Y			
Net Growth, Total	-3.20***				-5.88***				-5.62***			
	(1.19)				(1.48)				(1.29)			
Net Growth, Low Lev		-3.97***		-4.00***		-5.87***		-5.69***		-5.10***		-4.84***
		(1.21)		(1.40)		(1.33)		(1.42)		(1.22)		(1.26)
Net Growth, High Lev			-0.13	0.30			-2.33	-1.71			-2.98	-2.46
			(2.43)	(2.54)			(2.71)	(2.78)			(2.55)	(2.65)
R2	0.10	0.12	0.05	0.12	0.17	0.17	0.09	0.18	0.17	0.16	0.12	0.17
N	95	95	95	95	95	95	95	95	95	95	95	95

This table describes the regression results when breaking out movements in hedge fund exposures by ex-ante fund leverage type. Each month, high leverage funds are those that fall into the top 20 or 10% of balance sheet leverage (gross assets divided by net assets) in the cross-section, the quarter end prior to the month of interest. Control variables are included in the regressions but not displayed for brevity. The top panel classifies high leverage funds as those that fall in the top 20% while the bottom focuses on the top 10%. Coefficients are scaled to represent the basis point movement of yields with respect to a standard deviation movement in explanatory variables. Standard errors are provided in parentheses and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 11: **Notable Movements in HF Treasury Market Demand**

Rank	Year	Month	Multi-Strategy (% of Total)	Relative Value	Macro	Managed Futures	Equity	Total ($, billions)	Δy^{5Y} (b.p.)	Δy^{5Y}_{nonmp}
1	2013	12	63.93	11.02	4.13	26.95	-0.78	-106.11	36.29	37.00
2	2017	3	82.10	8.24	5.63	-0.37	-6.65	-78.96	2.65	16.12
3	2018	5	48.95	1.50	23.19	10.61	-0.86	78.63	-11.21	-9.88
4	2020	2	43.45	45.68	-9.67	10.86	4.16	77.74	-40.41	-40.41
5	2018	1	45.24	8.90	27.35	20.08	-7.71	-77.10	33.38	28.91
6	2015	10	50.97	-2.17	19.38	8.17	6.39	-75.99	15.56	-0.94
7	2013	5	5.30	43.27	12.34	9.56	2.34	-75.85	36.49	34.43
8	2015	3	89.93	-15.26	15.87	8.18	4.33	74.05	-13.14	3.62
9	2013	10	35.01	17.26	12.22	17.13	1.85	72.18	-8.23	-11.22
10	2014	12	42.98	9.97	29.89	9.63	-0.12	-70.19	14.96	30.20
11	2020	3	-112.99	109.30	33.08	19.16	6.91	-70.16	-47.12	-16.34
12	2015	1	13.66	55.58	24.58	2.20	-0.59	67.31	-46.93	-46.08
13	2019	4	77.66	-19.17	16.82	0.49	3.17	-65.60	4.80	4.80
14	2018	8	87.90	5.58	-9.26	5.16	-2.23	65.04	-9.26	-11.32
15	2016	1	83.15	2.34	1.05	23.76	2.31	64.92	-42.10	-36.65

This Table lists the top 15 months where absolute changes of net hedge fund exposures were at an all time high. The third column ("Total") from the right displays the raw change in net UST exposures scaled by gross Treasury return. The five columns to the left ("Multi-Strategy" through "Equity") display strategy-specific, scaled net exposure changes as a percentage of the total. The two columns on the right provide the basis point change in yield over the month and the change corrected for monetary policy surprises. See text for more details.

Table 12: **Aggregate Pricing of Hedge Fund Risk**

	Model 1		Model 2		Model 3		Model 4			
	IP	t(IP)	Infl	t(Infl)	HF	t(HF)	Infl	t(Infl)	HF	t(HF)
β_{1Y}	-0.06	-1.27	-0.01	-0.41	0.03	0.66	-0.02	-1.05	0.01	0.71
β_{2Y}	-0.06	-1.6	-0.06*	-1.72	0.08**	2.04	-0.06***	-2.67	0.07***	3.16
β_{3Y}	-0.07**	-2.15	-0.12***	-3.01	0.15***	3.32	-0.13***	-3.94	0.15***	4.06
β_{4Y}	-0.08**	-2.23	-0.19***	-3.42	0.23***	3.65	-0.2***	-4.2	0.23***	4.36
β_{5Y}	-0.08**	-2.02	-0.26***	-3.48	0.3***	3.71	-0.27***	-4.21	0.31***	4.51
β_{6Y}	-0.09*	-1.78	-0.33***	-3.5	0.36***	3.74	-0.35***	-4.23	0.39***	4.62
β_{7Y}	-0.1	-1.59	-0.4***	-3.54	0.42***	3.77	-0.42***	-4.29	0.45***	4.71
β_{9Y}	-0.1	-1.43	-0.47***	-3.61	0.47***	3.81	-0.48***	-4.38	0.51***	4.77
β_{9Y}	-0.11	-1.31	-0.53***	-3.68	0.52***	3.83	-0.55***	-4.48	0.55***	4.77
β_{10Y}	-0.11	-1.22	-0.59***	-3.74	0.56***	3.83	-0.61***	-4.58	0.6***	4.72
λ	-5	-0.48	-0.43	-1.16	0.62	1.16	-0.34	-0.68	0.11	0.24
Time Series Length	95									
Number of Assets	30									
Standard Errors	Newey-West with Bartlett Kernel Smoothing									

This table describes GMM estimation results of model parameters (return betas and factor prices of risk), when estimating the model in Equation 8. Each panel examines a different factor structure – (1) only industrial production growth, (2) only PCE inflation, (3) aggregate movements in hedge fund exposures, and (4) inflation and hedge fund exposures jointly. Parameter standard errors are provided in the second column of each panel and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 13: **Historical Pricing of Inflation Risk**

	Long Sample 1				Long Sample 2			
	Const	t(Const)	Infl	t(Infl)	Const	t(Const)	Infl	t(Infl)
β_{6M}	0.04***	6.4	0.01	0.63	0.04***	6.66	0	0.42
β_{12M}	0.07***	4.57	-0.03	-1.37	0.06***	4.7	-0.03	-1.59
β_{18M}	0.09***	4.11	-0.06**	-2.08	0.09***	4.21	-0.06**	-2.25
β_{24M}	0.11***	3.76	-0.09**	-2.48	0.1***	3.83	-0.08**	-2.55
β_{30M}	0.13***	3.72	-0.12***	-2.97	0.12***	3.82	-0.12***	-2.96
β_{36M}	0.15***	3.77	-0.15***	-3.29	0.14***	3.85	-0.14***	-3.22
β_{42M}	0.17***	3.81	-0.18***	-3.63	0.16***	3.88	-0.17***	-3.5
β_{48M}	0.17***	3.61	-0.2***	-3.6	0.17***	3.68	-0.19***	-3.45
β_{54M}	0.18***	3.49	-0.24***	-3.91	0.17***	3.54	-0.22***	-3.67
β_{60M}	0.18***	3.28	-0.25***	-3.81	0.18***	3.37	-0.23***	-3.57
β_{120M}	0.22***	3.29	-0.33***	-4.26	0.21***	3.38	-0.31***	-3.94
$\beta_{>120M}$	0.31***	2.91	-0.61***	-4.72	–	–	–	–
λ	0.07***	2.68	-0.43**	-2.25	0.05***	3.02	-0.56**	-2.19
Time Series Length	616				661			
Number of Assets	12				11			
Standard Errors	Newey-West with Bartlett Kernel Smoothing							

This table describes GMM estimation results of model parameters (return betas and factor prices of risk), when estimating the model in Equation 8 using historical bond return data. Each panel examines a different historical sample. Parameter standard errors are provided in the second column of each panel and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 14: **Pricing by Hedge Fund Strategy**

	Multi-Strategy		Relative Value		Macro		Managed Futures		Equity	
	Est	t(Est)	Est	t(Est)	Est	t(Est)	Est	t(Est)	Est	t(Est)
β_{1Y}	0.03*	1.75	-0.02	-1.04	-0.01	-0.64	0.03***	3.05	-0.01	-0.5
β_{2Y}	0.08***	2.81	-0.01	-0.3	0	-0.09	0.12***	6.49	-0.03	-1.55
β_{3Y}	0.13***	3.33	0.01	0.18	0.01	0.12	0.24***	8.47	-0.06**	-2.33
β_{4Y}	0.17***	3.26	0.04	0.5	0.02	0.27	0.38***	9.04	-0.08**	-2.41
β_{5Y}	0.2***	2.97	0.08	0.72	0.04	0.4	0.51***	9.03	-0.1**	-2.25
β_{6Y}	0.22***	2.67	0.13	0.9	0.07	0.52	0.63***	8.89	-0.12**	-2.08
β_{7Y}	0.24**	2.39	0.18	1.05	0.09	0.62	0.74***	8.73	-0.14*	-1.95
β_{8Y}	0.24**	2.16	0.23	1.19	0.12	0.7	0.83***	8.52	-0.16*	-1.87
β_{9Y}	0.25**	1.97	0.27	1.3	0.15	0.77	0.91***	8.25	-0.18*	-1.82
β_{10Y}	0.25*	1.81	0.32	1.39	0.18	0.83	0.98***	7.92	-0.2*	-1.8
λ	0.32	0.55	-0.32	-0.59	-0.42	-0.43	0.14	0.43	-0.47	-0.55
Time Series Length	95									
Number of Assets	30									
Standard Errors	Newey-West with Bartlett Kernel Smoothing									

This table describes GMM estimation results of model parameters (return betas and factor prices of risk), when estimating the model in Equation 8 using each strategy-specific time series of movements in hedge fund net exposures. Each panel examines a separte estimation for that strategy. Parameter standard errors are provided in the second column of each panel and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.

Table 15: **Pricing by Hedge Fund Leverage Type**

	Infl	t(Infl)	HF_lowlev	t(HF_lowlev)	HF_highlev	t(HF_highlev)
β_{1Y}	-0.02	-1.49	0.03**	2.33	-0.02	-0.88
β_{2Y}	-0.06***	-3.11	0.08***	3.47	-0.01	-0.12
β_{3Y}	-0.12***	-3.73	0.15***	4	0.02	0.25
β_{4Y}	-0.19***	-3.67	0.23***	4.22	0.05	0.51
β_{5Y}	-0.27***	-3.63	0.29***	4.26	0.09	0.69
β_{6Y}	-0.34***	-3.66	0.34***	4.22	0.13	0.82
β_{7Y}	-0.41***	-3.74	0.39***	4.15	0.16	0.91
β_{8Y}	-0.48***	-3.85	0.43***	4.07	0.2	0.97
β_{9Y}	-0.54***	-3.97	0.46***	3.98	0.23	1.02
β_{10Y}	-0.6***	-4.08	0.49***	3.88	0.26	1.05
λ	-0.8	-0.91	0.11	0.26	-0.84	-0.56
Time Series Length	95					
Number of Assets	30					
Standard Errors	Newey-West with Bartlett Kernel Smoothing					

This table describes GMM estimation results of model parameters (return betas and factor prices of risk), when estimating the model in Equation 8 using three factors simultaneously – inflation, changes in exposures for low leverage funds, and changes in exposures for high leverage funds. Parameter standard errors are provided in the second column of each panel and *, **, *** indicate significance at 10%, 5%, and 1% levels respectively. All standard errors account for auto-correlation in residuals (Newey-West). See text for more details.