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Research for Institutional Money Management

EDHEC-RISK Institute

INTRODUCTION

Introduction to EDHEC Research for Institutional Money Management supplement in P&I, April 2020

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I am delighted to introduce the latest EDHEC-Risk Institute special issue of the EDHEC Research for Institutional Money Management supplement to Pensions & Investments, which aims to provide institutional investors with an academic research perspective on the most relevant issues in the industry today.

In the first article, Professor Gianfranco Gianfrate discusses how the latest evidence about the magnitude of climate change risks demands faster and more decisive actions to mitigate the exposure of financial intermediaries and investors – and, as a consequence, of the real economy. There is a clear need to unleash financial engineering to manage climate risks. The role of financial markets and financial innovation as a mechanism to enforce climate policy and to accelerate the transition toward a low-carbon economy is still overlooked.

Our second article proposes a definition of value in Treasury bonds that allows for statistically significant and economically relevant predictions of cross-sectional excess returns. The value pricing factor exploits the differences between the market and theoretical values of Treasury bonds assessed using an economically justifiable Gaussian dynamic term structure model. A long-only version of the value strategy outperforms the market portfolio in terms of Sharpe ratio in 14 of the 15 three-year periods considered.

While factor investing and liability-driven investing relate to two separate strands of the academic literature, a strong case can be made for combining these approaches. Each of the three steps of a liability-driven investing process, namely the construction of a well-rewarded performance-seeking portfolio, the construction of a safe liability-hedging portfolio and an efficient allocation to these building blocks, can be better addressed by taking a factor perspective. Our third article can be regarded as a first step toward the introduction of a comprehensive investment framework blending liability-driven investing and factor investing.

We introduce a method to create two interpretable liquidity measures, which we associate with market and funding liquidity. This involves creating two parsimonious linear combinations of the many liquidity proxies often used in the liquidity literature. Our construction does not require transaction-level data (such as volume or bid-offer spreads), but correlates well both with other measures that do, and with other liquidity proxies (liquidity as "noise," liquidity as broker-dealer leverage) recently introduced in the literature.

Finally, we examine the question of cross-sectional momentum in the U.S. sovereign bond market. We show that long-short duration-adjusted cross-sectional reversal strategies are significantly profitable over an extended range of lags and illustrate a possible application of this result in a long-only framework. We link the profitability to two factors: (i) the ability of the duration-adjustment procedure to single out winners and losers through their exposure to slope changes, and (ii) the degree of mean-reversion of the slope.

We hope that the articles in the supplement will prove useful, informative and insightful. We wish you an enjoyable read and extend our warmest thanks to P&I for their collaboration on the supplement.

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A Look at the Landscape for Climate Change Finance

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- **The transition toward a low-carbon economy will require profound innovations in the way the global financial system manages climate-related risks.**
- **The initiatives to enhance the transparency of climate exposures of banks and asset managers are only the first step in the process of making the financial system resilient to climate risks.**
- **Financial markets do appear to lack the tools and instruments needed by investors and financial intermediaries to effectively deal with climate risks.**
- **Policymakers should create the conditions to facilitate climate-related financial innovations.**

As climate change and global warming are addressed by tougher regulations, new emerging technologies and shifts in consumer behaviors, global investors are increasingly treating climate risks as a key aspect when pricing financial assets and deciding the allocation of their investment portfolios. So far, the main focus of institutional investors has been on whether policies on carbon emissions will strand the assets of investee fossil-fuel companies. For example, the Norwegian sovereign wealth fund – one of the world's largest institutional investors – announced in November 2017 that it was divesting from its oil and gas stocks.

However, new estimates are shedding light on the broader indirect impact of climate change on the value of assets held by banks and financial companies. Dietz et al. (2016) show how a leading integrated assessment model can be used to quantify the expected impact of climate change on the present market value of global financial assets. They find that the expected "climate value at risk" of global financial assets today is 1.8% along a business-as-usual emissions path, which amounts to US$2.5 trillion – although for the 99th percentile the estimate rises to US$24.2 trillion. Importantly, Battiston et al. (2017) find that while direct exposures to the fossil fuel sector are low (3-12%), the combined exposures to climate policy-relevant sectors are high (40-54%), heterogeneous and amplified by large indirect exposures via financial counterparties. In other words, there are climate change-related risks borne by the global financial system that are similar in magnitude to those that emerged in the financial crisis.

As a sign of regulators' growing concern about climate change as a source of risk for the global financial system, the Task Force on Climate-related Financial Disclosures (TCFD) created by the Financial Stability Board (FSB) recently advised[1] global organizations to enhance their financial disclosures related to the potential effects of climate change.

Still, transparency is only the first step. As carbon risks appear more pervasive and material for the financial system than previously thought, the compelling issue for investors is how to manage or neutralize such risks once they have been identified and quantified. If investors do not want to retain carbon risk – by covering the potential losses out of the capital invested – what are the possible strategies?

Current Approaches to Reduce the Exposure to Climate Risks

The quest for tools and approaches that could insulate investment portfolios from environmental risks (and also from other societal risks generally) is nothing new, and over time entire segments of the financial industry have emerged to offer "sustainable," "green," or "responsible" financial products. With a focus on carbon risks, the two main approaches appear to be 1) divesting and 2) exercising active ownership.

Divesting or avoiding investments in companies significantly exposed to carbon risks is assumed to result in the substantial "decarbonization" of the investment pool. Some international initiatives – notably, Gofossilfree and the Portfolio Decarbonization Coalition (PDC) – are underway to promote such approaches among institutional investors and asset managers. Investors committed to decarbonizing their portfolios typically, on the one hand, implement negative screening in order to identify companies whose operations are exposed to fossil fuels, and, on the other, enhance investments in renewable energy (solar, wind, geothermal, hydro and tidal power), enabling technologies (electric vehicles, smart grids), energy efficiency (LED lighting, more efficient motors, smart energy management technologies) and products and activities that reduce energy usage (recycling, insulation, battery storage).

However, as PDC reports,"There has been relatively little innovation in terms of the opportunities being presented to them, in particular beyond equities and clean energy," and "there are relatively few investment managers with a strong track record on decarbonization, and they find that there is an insufficient choice of low-carbon opportunities across asset classes." Apart from the paucity (relative to the size of institutional portfolios) of carbon-free assets, the decarbonization strategy presents several implementation shortcomings. Notably, the identification of the assets exposed to carbon risks is to a certain extent subjective because it depends on the metrics adopted. For example, the outcome can vary significantly depending on whether the exposure is measured from a Scope 1, 2, or 3 perspective.

Some financial institutions are trying to curb their exposure to climate risk by exercising their voting rights at shareholder meetings and by engaging directly with the company at management and board level. "Active ownership" builds on the assumption that it is the responsibility of a long-term shareholder to question the robustness of financial analyses behind significant new investments made by investee entities. Since fossil fuel companies face the prospect of business decline and must adapt to new circumstances to survive, active ownership by investors may push them to leverage their present strengths toward a low-carbon energy production system. Since this transition will take time, entities exposed to carbon risks will need the engagement and support of large long-term investors. By engaging on climate resilience and transition strategies for fossil fuel companies, investors who adopt active ownership can manage their portfolio's exposure to climate change risks and protect the long-term value of their investments.

Active ownership engagements are conducted either independently or through collaborative initiatives such as CDP (Carbon Disclosure Project) and the major climate change investor networks – the European Institutional Investors Group on Climate Change (IIGCC), the Asia Investor Group on Climate Change (AIGCC), the Australia/New Zealand Investor Group on Climate Change (IGCC) and the Investor Network on Climate Risk (INCR). Typically, these initiatives aim to encourage companies to disclose their climate change strategies (CDP information requests), set emission reduction targets, and take action on sector-specific issues such as gas flaring in the oil and gas sector. As a recent example of collaborative engagement on climate-related risks, in May 2017, 63% of Exxon Mobil shareholders approved a proposal at the company's AGM calling for the world's largest listed oil producer to improve its disclosure on business risks through global climate change policies.

Rising demand from investors to assess sustainability-related risk and opportunities has fueled the strong growth of the sustainability information market over the last two decades. A range of asset managers use sustainability analyses and ratings in managing their portfolios by comparing quantitative metrics and consolidated scoring for their investment universes.

Sustainability research and analysis assesses the environmental, social and governance (ESG) performance of corporations and other issuers of securities such as local governments and sovereign States. ESG ratings, rankings and indexes aim to measure the performance and risk of issuers against ESG criteria. They therefore provide a proxy for the external costs and benefits beyond

[1] https://www.fsb-tcfd.org/wp-content/uploads/2016/12/16_1221_TCFD_Report_Letter.pdf.

conventional financial accounting and reporting parameters (Laermann, 2016).

In practice, by establishing an overall score that positions the company on a particular scale, ratings indicate a company's sustainability performance. Investors, depending on their specific selection approach, can use such ratings or grades when mapping and managing investment portfolios.

While company engagements and sustainability ratings have helped investors understand and possibly reduce their exposure to environmental risks, the scope and pervasiveness of the problem call for more decisive action.

The Tools Needed to Decarbonize Investments

In a context where carbon is priced dynamically, carbon exposure affects the volatility of investment portfolios as well as their long-term returns. A portfolio management strategy that seeks to maximize portfolio returns as its primary goal may be quite different from one that seeks to reduce overall portfolio risk. But whatever the goal, as for other sources of risk, the strategy should be consistently designed, implemented and evaluated against the primary objective: return impact or risk reduction (Statman, 2005). Setting one objective and then evaluating the results against another could be inconsistent and counterproductive.

The reduction of carbon risks should be a key objective for at least three major categories of financial institutions. First, banks – and especially the "systematically important" ones – need to quantify and manage carbon risks in order to prevent shocks which may potentially not only affect their liquidity and solvency but also pose systemic threats to the financial markets and real economy. Second, the investors who provide financial products and services marketed as "green" or "sustainable" should be able to fully embed effective carbon reduction in what they commit to delivering to clients. Finally, long-term oriented institutional investors have a particularly strong incentive to proactively manage climate risks. Given that financial institutions such as pension funds and sovereign wealth funds have a long-term investment horizon, the likelihood of the materialization of carbon risks affecting their assets is higher. These three categories of investors together represent a large portion of modern global finance.

In order to conceptualize the ways in which these investors can deal with carbon risks, Figure 1 represents the relationship between portfolio value and the cost of carbon. We consider that for an investment portfolio comprising assets (in total or in part) exposed to carbon risks, the relationship between value and carbon price is negative and we assume that such a relationship is linear (Figure 1.a).[2]

In their traditional framework, Bodie and Merton (2000) identify three possible approaches to achieving reduced or zero risks. The most intuitive one is risk avoidance, which entails deliberately avoiding asset risks by excluding those securities and financial instruments that carry them. Using the language and the framework introduced in the previous paragraphs, such an approach would involve negative screening and lists excluding big carbon polluters so that (as shown in Figure 1.b) the portfolio value becomes insensitive to any variation in the carbon price.

The second possible approach is the hedging against carbon risk. Formally, a risk is hedged when the action taken to reduce the portfolio's exposure to a loss also causes the investor to give up on the possibility of a gain from a favorable configuration of the risk source (Bodie and Merton, 2000). Hedging therefore usually involves "linear" instruments whose contractual payoffs move one-for-one with the value of the underlying asset and so can be graphed with a straight line (Figure 1.c). Such linear contracts tend to be obligations or commitments usually in the form of forwards, futures and swaps (Servaes et al., 2009), but the construction of synthetic positions that deliver the same payoff as a hedging strategy is also possible.

Andersson et al. (2016) present an alternative strategy to hedge against climate risk, one that optimizes the composition of a low-carbon portfolio index so as to minimize the tracking error with the reference benchmark index. They show that tracking error can be almost eliminated even for a low-carbon index that has a 50% lower carbon footprint. By investing in such an index, investors are in effect holding a "free option on carbon": as long as the introduction of significant limits on carbon emissions is postponed, they are essentially able to obtain the same returns as on a benchmark index, but the day when carbon emissions are priced, the low-carbon index will outperform the benchmark (Andersson et al., 2016).

The third relevant risk management strategy is insurance. This eliminates only the adverse outcome, while maintaining potential upside, but either an upfront premium or ongoing costs are required.

Insurance contracts tend to involve "non-linear" contracts (Servaes et al., 2009) whose payoffs are not graphed as a single straight line, but rather a combination of lines. In the language of derivatives finance, the insurance scheme represented in Figure 1.d would be the payoff of a put option which gives the investor the right, but not the obligation, to purchase carbon at a fixed price.

As of now, the financial system lacks the instruments to efficiently hedge and insure against carbon risks. The space for switching from carbon-risky to carbon-free assets is also very limited. Carbon-free securities such as green bonds are growing steadily and the Luxembourg Stock Exchange recently launched a Green Exchange entirely devoted to sustainable securities. Still, these innovations have so far had very limited scope and may not prove efficient for the implementation of hedging strategies.

On the other hand, carbon-negative assets do already exist. Carbon permits in cap and trade systems or the financial contracts related to the REDD and REDD+ schemes are among the most notable examples. However, investors currently have no access to such assets. If the financial system moves – autonomously or because of regulation – toward the implementation of effective risk management policies for such risks, financial innovations – for instance, the securitization of the REDD schemes or the creation of climate and carbon-related derivative securities – would be necessary. Moreover, carbon-neutral vehicles and indexes can be designed to make climate risk hedging more effective and accessible to institutional and individual investors. Importantly, carbon risks are not only attached to the securities issued by companies but also to those (mostly fixed income) issued by governments. Considering that government bonds are the most relevant asset class held by most institutional investors, the need to insulate such bonds from carbon risks is becoming more and more apparent.

It is difficult to determine ex-ante which products, intermediaries and financial instruments will best serve the need for the management of climate risks. Assuming a functionalist view of the financial system (Merton and Bodies, 2005), the focus should be more on functions than on individual products. The functional perspective views financial innovation as driving the financial system toward the goal of greater economic efficiency, including eco-sustainability.

Innovation will result either in new specialized intermediaries or in new markets serving the need for protection against climate risk. Intermediaries will emerge as the solution if climate-related products remain low-volume and highly customized. On the other hand, if the products become standardized, they will move from intermediaries to markets. In this case, as the volume of traded securities expands, the increased volumes will lower the transaction costs, thus facilitating the design and launch of new products. The success of these markets and custom products will stimulate further investments in creating additional products and trading markets (Merton and Bodie, 2005), progressively spiraling toward low transaction costs and dynamically complete eco-sustainable markets.

Unleashing Climate-Related Financial Innovation

The latest evidence about the magnitude of climate change risks demands faster and more decisive actions to mitigate the exposure of financial intermediaries and investors – and, as a consequence, of the real economy. As of today, renewables, timber and forestry, sustainable agriculture investments, and clean-tech ventures can provide only limited hedges for financial institutions. While instruments like green bonds are gaining momentum, they still channel no more than a minor fraction of the total financial resources needed to be mobilized to achieve the Paris Agreement goals.

There is a clear need to unleash financial engineering to manage climate risks. Policymakers should further promote financial climate-related disclosures for companies and financial intermediaries.[3] Beyond

[2] An analysis that defines the negative relation between (a randomly selected) equity portfolio value and carbon cost is provided by Credit Suisse's report, "Investing in carbon efficient equities: how the race to slow climate change may affect stock performance", 2015.
[3] Mandatory transparency has been implemented in France and could be enacted at banks in the European Union.

transparency, policymakers should recognize the key role the financial system could play in pricing carbon and in allocating capital toward lower-emission companies. Stable and predictable carbon-pricing regimes would significantly help foster financial innovation that could further accelerate the de-carbonization of the global economy even in countries which are more lenient in implementing climate mitigation actions.

The role of financial markets and financial innovation as a mechanism to enforce climate policy and to accelerate the transition toward a low-carbon economy is still overlooked. •

EXHIBIT 1

Immunizing investment exposure from carbon risk

Figure 1 represents the relationship between portfolio value and cost of carbon. For a portfolio comprising assets (in total or in part) exposed to carbon risk, the relationship between value and carbon price is negative and assumed to be linear (Figure 1.a). Figure 1.b shows a portfolio whose value would be insensitive to any variation in the carbon price. Hedging is carried out with "linear" instruments whose contractual payoffs move one-for-one with the value of the underlying asset, and therefore can be graphed with a straight line (Figure 1.c). Insuring (Figure 1.d) tends to involve "non-linear" contracts whose payoffs are not graphed as a single straight line, but rather a combination of lines (Servaes et al., 2009).

Figure 1.a

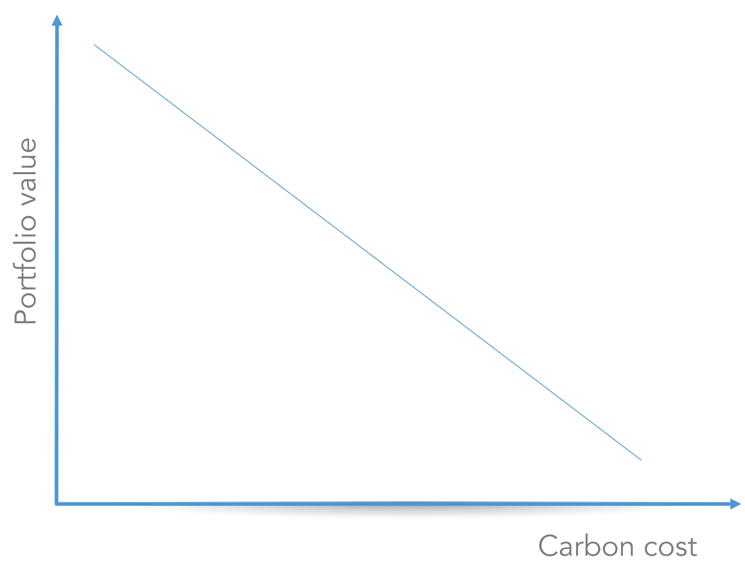


Figure 1.b Full decarbonization

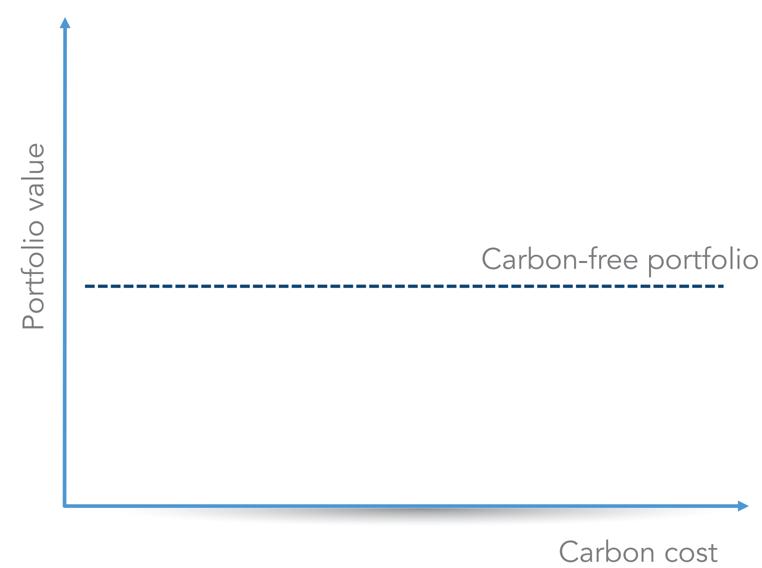


Figure 1.c Hedging

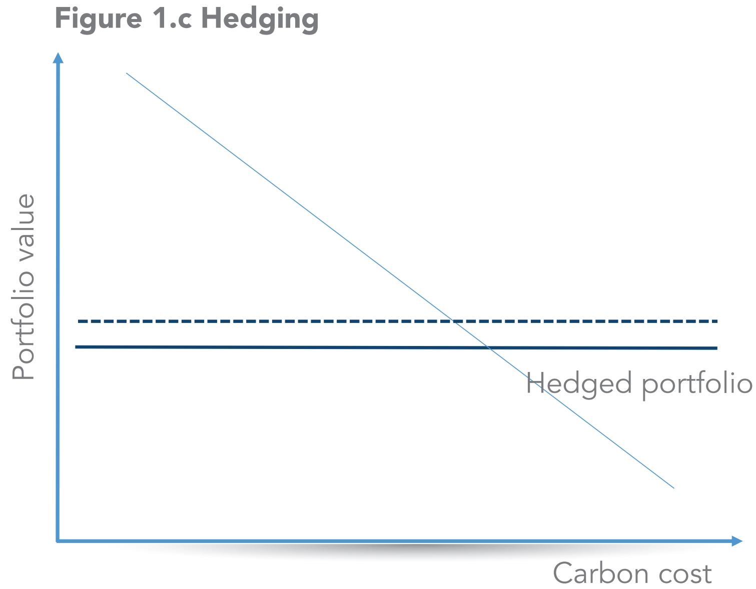
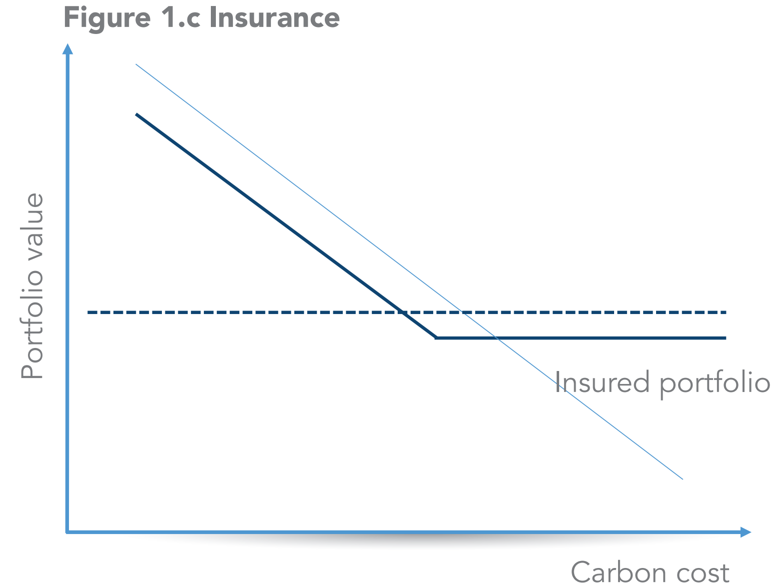


Figure 1.c Insurance



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Defining and Exploiting Value in U.S. Treasury Bonds[4]

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- **This article proposes a definition of value in Treasury bonds that allows for statistically significant and economically relevant predictions of cross-sectional excess returns.**
- **The value pricing factor exploits the differences between the market and theoretical values of Treasury bonds assessed using an economically justifiable Gaussian dynamic term structure model.**
- **A long-only version of the value strategy outperforms the market portfolio in terms of Sharpe ratio in 14 out of the 15 three-year periods considered.**

Value has been recognized as one of the most important factors for equities at least since the pioneering work by Fama and McBeth (1973). In equities, the ratio of book-to-market value has traditionally been used as a proxy for the value factor. Natural as this choice is for this asset class, it is difficult to translate the concept of value to the fixed-income domain, and for this reason Fama and French (1993) argued that value does not apply to fixed-income instruments in general, and to Treasury bonds in particular.[5] This seems to be at odds with recent literature, which claims to have found value (and momentum) "everywhere."

The "problem with value in bonds" is rendered more acute by the rather ad hoc definitions of value used for fixed-income instruments. For instance. Asness, Moskowitz and Pedersen (2013) defined value for bonds as the (negative of the) five-year bond returns – a choice motivated by the observation that in equities, this difference in returns is found to be positively correlated with the book-to-market ratio.[6] The factor thus defined may well predict future bond returns, but its interpretation as "value" seems at least a stretch, and one, if not two, steps removed from the true latent underlying factor. At best, it plays the role of a proxy, and as a result labeling the chosen measure as value becomes rather arbitrary.

In this article we provide what we think is a more intuitively satisfactory definition of value in U.S. Treasury bonds, and we show that the value quantity we define has very strong predictive power of future cross-sectional Treasury returns. More precisely, we identify "cheap" ("valuable") and "expensive" bonds using a dynamic Gaussian term structure model, and show that a systematic, no-peek-ahead strategy of investing in the cheap bonds and shorting the expensive ones has a strongly positive Sharpe ratio. Our results are so robust that, before and after adjusting for duration exposure, the strategy we propose has positive Sharpe ratios for 14 out of the 15 three-year periods from 1975 to 2017, a Sharpe ratio which is statistically significantly different from zero at the 99.9% confidence level in 13 of the 15 three-year sub-periods, and an average Sharpe ratio (before transaction costs) above 1.

Dataset

The data used for the study is made up of the close-of-business day prices prices of 1,562 US Treasury coupon bonds over the period Dec. 27, 1973, to June 29, 2018.[7] All these bonds are non-callable, non-puttable and non-inflation linked. We also excluded prices of individual bonds that were deemed to be erroneous from the dataset. This was determined by setting a threshold in standard deviations for the price changes, and then excluding those bonds whose price move exceeded the threshold while the other bonds in the universe for that day did not show a similar move. We stress that this culling procedure is conservative because spurious spikes would generate fictitious profits; we therefore prefer to miss a true sharp price deviation/reversal than to include a fake one.

Interest Rate Model

The affine model we employ can be defined in the physical (P) and risk-neutral (Q) measures. Starting from the P measure, it can be written as:

$$dr_t = \kappa_t^P (\theta_t^P - r_t)\, dt + \sigma_t\, dw_t \qquad (1)$$

$$d\theta_t = \kappa_\theta^P (\theta_\theta^P - \theta_t)\, dt + \sigma_t\, dw_\theta \qquad (2)$$

$$E\,[\, dw_t\, dw_\theta\,] = \rho dt \qquad (3)$$

The model can be interpreted as describing the actions of the monetary authorities who respond to deviations of the inflation and/or output gap from their desired target levels by adjusting the Fed Funds rate (in our model, the '"short rate'") towardstoward the long-term NAIRU-compatible[8] nominal rate (the ultimate reversion level θ_θ; they do so, however, with a degree of urgency ('"aggressiveness'") that depends on the economic conditions of the moment; the adjustment is therefore achieved by letting the short rate revert to a time-dependent reversion level, which in turn reverts towardstoward the unchanging NAIRU-compatible long-term nominal rate, θ_θ. In moving from the physical to the risk-neutral measure, we assume that investors only seek compensation for level risk (see, in this respect, Cochrane and Piazzesi, 2005; Adrian, Crump and Moench, 2010), and therefore modify the P-measure dynamics in Equation (2) as:

$$d\theta_t = \kappa_\theta^P (\theta_\theta^P - \theta_t)\, dt + \lambda_t\ (r_t, \theta_t) + \sigma_\theta\, dw_\theta \qquad (4)$$

In general, the market price of risk could depend on both state variables. We make the assumptions
1) that the slope of the yield curve accounts for the degree of predictability associated with the business-cycle variation of risk aversion; and
2) that the additional predictability afforded by the new-generation return-predicting factors (e.g. Rebonato and Hatano, 2018; Cieslak and Povala, 2010) is due to deviations from fundamentals, and not to non-level rewarded risk factors.

Since our approach tries to capture precisely these deviations from fundamentals, we do not add other contributions to the market price of risk other than its business cycle/slope-related component. If we want to retain the essentially affine formulation, the market price of risk must display, at most, an affine dependence on the state variables. In other words, it must have the following form:

$$\lambda_t = \lambda_0 + \Lambda x_t \qquad (5)$$

We assume λ_0=0 – see Duffee (2002) for a justification of this choice. Cochrane and Piazzesi (2005), as well as Adrian, Crump, and Moench (2013) document that investors only seek compensation for bearing level risk. Given the high reversion speed of the short rate, we therefore impose the condition that only the uncertainty about the reversion level, θ_t, should attract a risk premium. This implies that the process for the short rate should be the same under P and Q. Finally, we require that the market price of risk should depend on the slope of the yield curve (Fama and Bliss, 1987; Campbell and Shiller, 1991). More details

[4] *This research has been supported by Amundi as part of the ETF, Indexing and Smart Beta Investment Strategies research chair at EDHEC-Risk Institute.*
[5] *"… explanatory variables like size and book-to-market equity have no obvious meaning for government and corporate bonds …"*
[6] *"… [we] show that individual stock portfolios formed from the negative of past five-yearfive-year returns are highly correlated with those formed on BE/ME ratios in our sample. […] Hence, using past five-year returns to measure value seems reasonable …"*
[7] *We thank ICE for providing us with the dataset used for our empirical analysis.*
[8] *The NAIRU is the non-accelerating inflation rate of unemployment, i.e, the unemployment rate which produces neither inflationary nor deflationary pressures.*

on the model formulation, the connection between the real-world and the pricing measure and the model calibration can be found in Rebonato, Maeso and Martellini (2019).

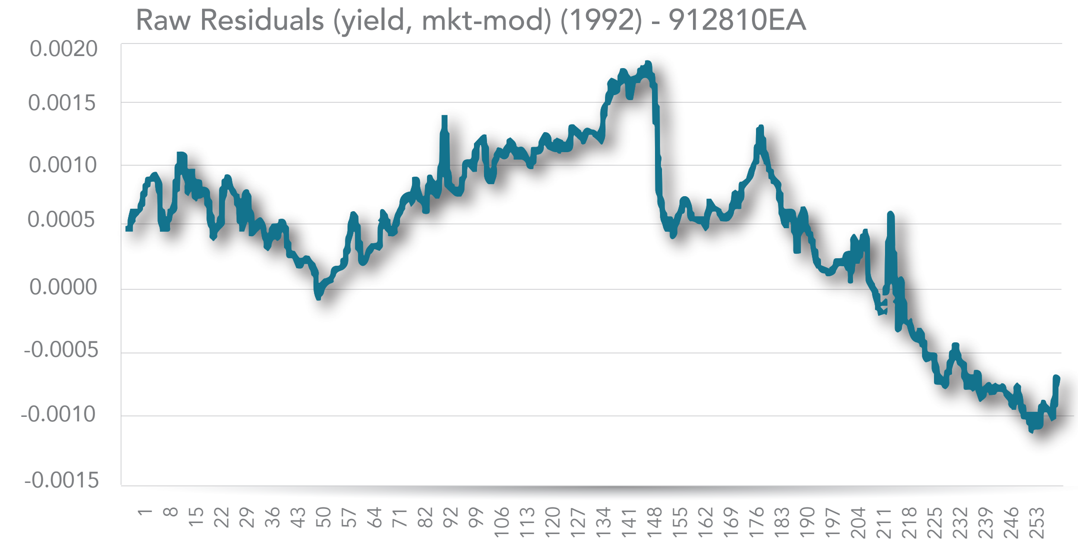
The model prices of the coupon bonds are calculated as:

$$CP_{mod_i}^{T_N} = \sum_{i=1}^{N} cashflow_i \; P_t^T \qquad (6)$$

where $CP_{mod_i}^{T_N}$ denotes the time-t price of a T-maturity coupon-bearing bond with N coupons still to pay, $P_t^{T_i}$ signifies the time-t price of a discount bond of maturity T_i, and the cash flows include both the coupons and the final repayment at maturity.

EXHIBIT 1

The Time Series of the Raw Pricing Error for CUSIP 912810EA



Creating the Strategy Signal

After the calibration procedure has been carried out, for each bond we have a time series of pricing errors. One such series for a particular Treasury bond is shown in Exhibit 1. To establish a trading strategy, we create a trading signal by setting the notional of the position in each bond to be proportional to the strength of the signal for that bond on that day. For each bond, the trading signal is formed by taking the difference between a slow-moving average and an adjusted fast-moving average of price errors. The adjusted fast-moving average is obtained by summing the last n_{short} price errors, and dividing the sum by n_{long}, rather than n_short, where n_{long} and n_{short} are the number of price errors in the long and short sum, respectively. We use a slow-moving average, rather than the zero level, for the pricing errors because some bonds (perhaps for liquidity or other reasons) may have an unconditional average price error different from zero. The reason for using an adjusted fast-moving average, – that is, for dividing the short sum by n_{long}, rather than n_{short} , – is to make the signal more stable and to filter out high-frequency (quickly reversed) price errors, clearly visible in the time series displayed in Exhibit 1, that can lead to overtrading. The differences in signal using a proper and an adjusted moving average are shown in Exhibit 2, which was obtained using a random walk to obtain the price errors, n_{long}= 20 and n_{short} t= 5. It is clear that the adjusted signal retains the salient trends, but removes the high-frequency fluctuations, which is exactly what we wanted to achieve.

We took the number of days in the slow-moving average as equal to 22 business days (corresponding to roughly one month), and the number of days in the fast-moving average ranging from 1 one to 5 five business days (with the last choice corresponding to roughly one week).[9]

We stress that the results we report in the following section were not obtained for any optimized combination of days in the fast- and slow-moving averages: as the round numbers (22 and one 1 or five5) and their simple interpretation (one month and one day/one week) indicate, we did not engage in a data-mining exercise of optimization. The same applies to the cut-off maturities (2 two and 15 years).

Typical patterns for the two moving averages and the resulting signal are shown in Exhibit 3. As this exhibit shows, the trading signals tend to display mean-reverting behavior, with reversion speeds implying half-lives of several weeks to a few months. This observation is important, because it suggests that the signal is practically exploitable, in that it neither requires excessively long strategies nor overly frequent rebalancing.

On any given day, our strategy will consist of long positions in cheap bonds and short positions in expensive bonds. The resulting portfolio will not have a systematic long or short bias but, on any given day, it will not have exactly zero cost, nor will it be exactly duration neutral. Because yields fell considerably over the period under study, we control for a possible residual duration exposure in our portfolio by calculating the net portfolio duration, and by subtracting the hypothetical profit (or loss) that a portfolio with that residual duration would make given the change in average yield from one day to the next. We note that subtracting the duration exposure this way would flatter the results from long positions, and penalize short positions, because achieving physical (as opposed to virtual) immunization requires selling an actual bond. Over the period under study, Treasuries have commanded an unconditional positive risk premium, and therefore physical hedging requires paying, rather than receiving, this premium. (To give an idea of the size of the effect, the magnitude of the unconditional risk premium for the 10-year point is over 200 basis points per annum.) To compensate for this, we increase the funding cost by an amount required to ensure zero realized return in each three-year period for a virtually duration-neutralized equal-weight long bond portfolio. We funded the difference between the proceeds from the short sales and the cost of the long positions by borrowing or lending at the Treasury Bill rate. Finally, we reinvested all coupons received in the same bond from which they originated.

Profitability of the Strategy

We carried out our analysis of the results by splitting the data into 15 blocks of three years (the last block is slightly shorter than three years). We have no return results for the first few days of each three-year block because of the need to build the moving average needed for the signal. On any given day, the overall strategy[10] will in general consist of long and short positions in different bonds. Exhibit 4 shows the cumulative profits for the duration-corrected strategy. The ratio of the strategy returns and volatility, i.e., the Sharpe ratio of the funded, duration-neutralized strategy, is shown in tabular form in Exhibit 5. We stress that the Sharpe ratio is positive in 14 out of 15 of the three-year blocks is often very high, is never significantly negative, and is significantly greater than zero at the 99.9% confidence level in 12 out of 15 blocks. It is clear that the Sharpe ratio of the strategy is very high, but also that it has tended to decline over time. By far the most interesting observation, however, is high correlation (75%) between the short-rate volatility (either as obtained from the fitting of the model, or as estimated statistically as the volatility of the three-month Treasury Bill rate) and the profitability of the strategy, displayed in Exhibit 6. We also note that the strategy tends to produce high returns (but not necessarily high Sharpe ratios!) when the market volatility is high; in these periods, the volatility of the strategy is also high, and therefore the Sharpe ratios do not display this link with the market volatility. This finding is significant because it suggests a clear indication of the origin of the profitability of the strategy. Our results can, in fact, be reconciled with the findings by Hu, Pan and Wang (2013), who establish a link between price errors (“noise” in their terminology, p. 2341) for Treasury bonds and a general decrease in market liquidity. The explanation they offer is that the greater the decrease in liquidity, the greater the difficulty encountered by pseudo-arbitrageurs in carrying out the trades that should bring Treasury prices in line with fundamentals. To the extent that an increase in volatility can be associated with a decrease in market liquidity, the findings of our study are consistent with the interpretation in Hu, Pan and Wang (2013), and provide a rationale for the source of profitability of our strategy. And if high returns are indeed achieved in periods of high market volatility, it is not surprising that in these periods the volatility of the strategy should also be high, as the deviations from fundamentals may well increase (giving rise to temporary losses) before eventually decreasing toward their reversion level.

Long-Only Analysis

We also explored a long-only version of our strategy by only investing in those bonds that, according to the model, were underpriced (cheap), and investing an equal amount in all the bonds in the universe (we call this the equal-weight portfolio). The market and strategy portfolios were sized to require the same outlay of cash, and both versions of the strategy were funded and duration-neutralized as explained in the previous section. We report the results in Exhibit 7. As mentioned, the funding rate was adjusted in each three-year block so as to give a zero Sharpe ratio for the long-only equal-weight portfolio. In terms of Sharpe ratio, the long-only strategy outperforms the market portfolio in 14 out of the 15 three-year periods. The average Sharpe ratio for the strategy is significantly higher than that of the long always strategy at the 99% confidence level. Although,

[9] We analyzed the robustness of our results using several values for the number of days in the slow and fast moving averages, and we found the results to be largely insensitive to reasonable variations from our chosen values

[10] In what follows, we omit the “duration-corrected” qualifier unless required for clarity.

from the theoretical point of view, these results do not add much to the results shown in the "Profitability of the Strategy" section, they are very important for the practical applicability of the strategy for many institutional investors, who often have long-only constraints.

CONCLUSION

In this article, we have proposed a definition of value in Treasury bonds that, we believe, displays more clearly the features intuitively associated with the term "value" than what has recently been offered in the literature. In our definition, value is the difference between the market price of a Treasury bond and its theoretical price, with the latter determined by a financially motivated dynamic Gaussian term structure model. Using this definition of value, we construct long/short self-financing portfolios that load positively/negatively on our value factor. After controlling for residual duration exposure, we show that the portfolios thus constructed consistently earn a very attractive Sharpe ratio (average Sharpe ratio of 1.03, with a positive Sharpe ratio in 14 of the 15 three-year periods in our dataset). The Sharpe ratio of a long-only version of the strategy outperforms that of an equally weighted long portfolio by 0.822. We have shown that the profitability of the strategy is closely linked to the volatility of the three-month Treasury Bill.

We can explain this finding if we establish a link between higher market volatility and poorer market liquidity. In this account of our finding, in periods of market turmoil (of high volatility), less arbitrage capital is forthcoming to bring prices back to fundamentals, and pricing errors temporarily appear. As market conditions revert to normal, the pricing errors are arbitraged away toward zero.

Our study did not try to account for trading costs, but, given the size of the Sharpe ratio, it appears unlikely that trading costs in the extremely liquid Treasury market could wipe out, or significantly reduce, the profitability of the strategy.

Finally, it would be interesting to undertake a systematic study of the timing of the profitability of our strategy, compared with the returns from a diversified U.S. equity index, or from the various equity factors that have been identified in the literature. We leave this as a possible future development. •

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EXHIBIT 2

The Time Series of the Signals Obtained Using a 'Proper' and an Adjusted Moving Average

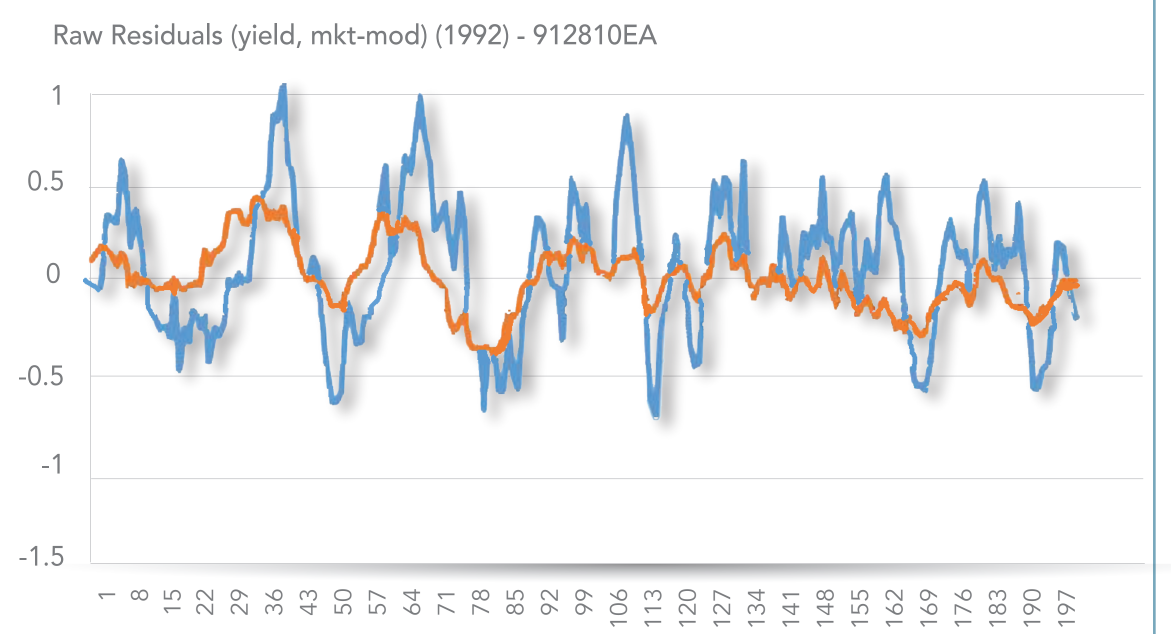

EXHIBIT 3

20-day and 5-day Moving Averages for CUSIP 912810CU and Their Difference (Top Panel), and the Associated Trading Signal (Bottom Panel)

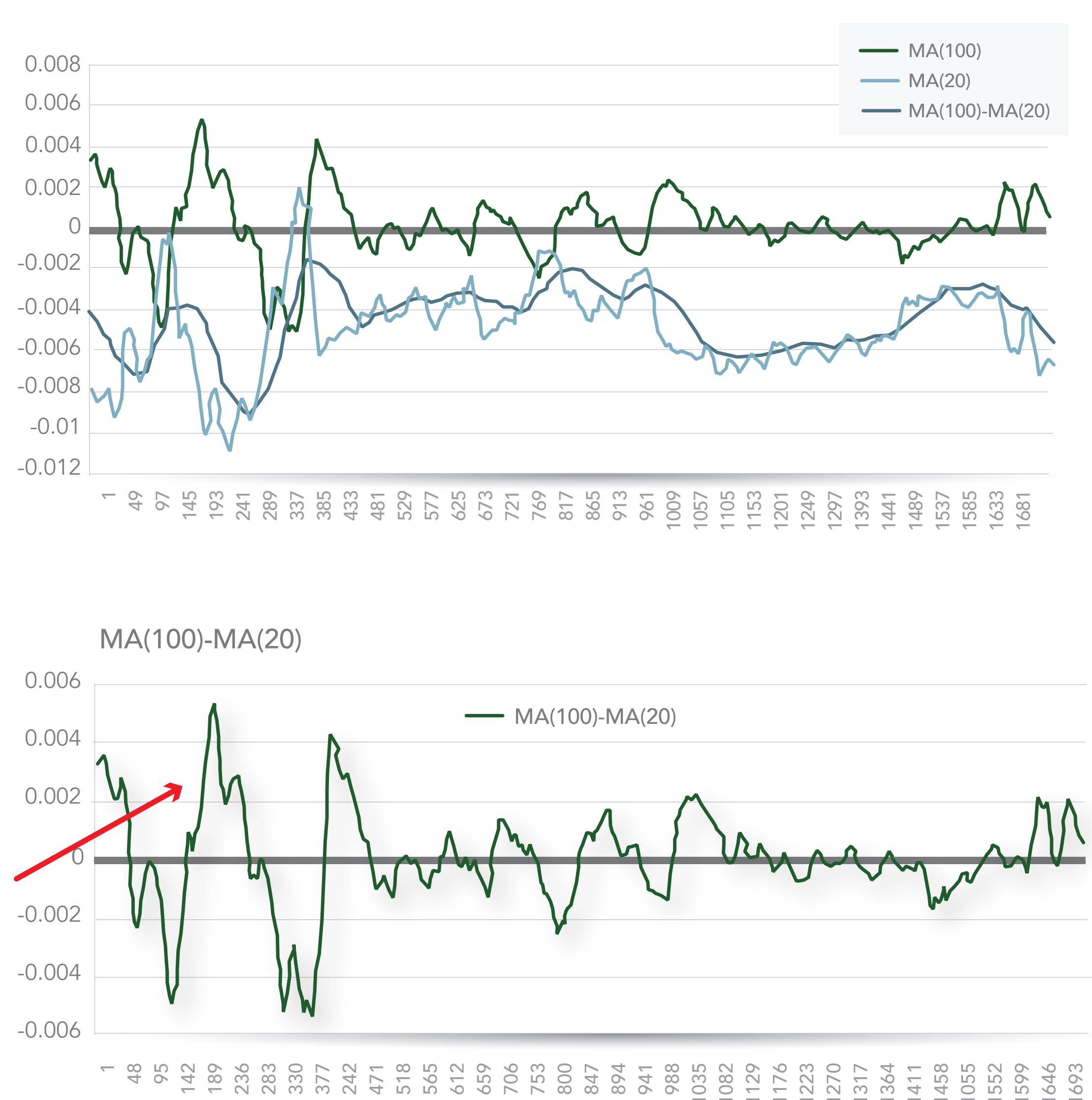

EXHIBIT 4

Cumulative Profit from the Strategy, Added Across All the Individual Bonds

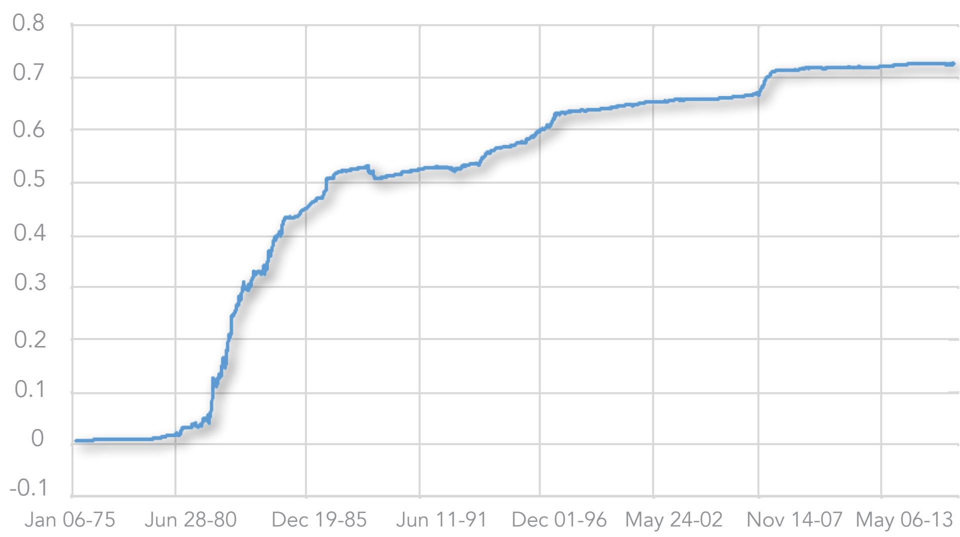

EXHIBIT 6

Rolling Returns and Standard Deviation of the Strategy (Left-Hand y-Axis) and Volatility of the ThreeMonth Treasury Bill (Right-Hand y-Axis)

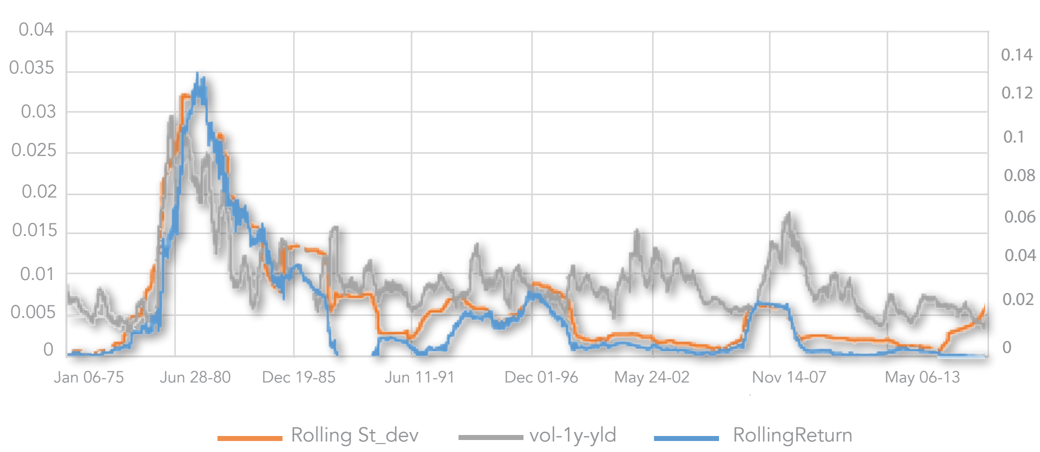

EXHIBIT 5

Sharpe Ratios for the Strategy in the 3-year Block in the Left Column for 2 and 20 Days in the Short and Long Moving Averages

Date	Difference in Sharpe Ratio
1975-1977	0.563
1978-1980	0.573
1981-1983	1.348
1984-1986	1.820
1987-1989	1.081
1990-1992	1.235
1993-1995	-0.014
1996-1998	0.110
1999-2001	1.282
2002-2004	0.691
2005-2007	0.326
2008-2010	2.716
2011-2013	0.086
2014-2016	1.812
2017-2018	1.121

EXHIBIT 7

Difference in Sharpe Ratios between the Long-only strategy and the equal-weight portfolio for the periods shown in the left-hand column

Date	Difference in Sharpe Ratio
1975-1977	0.197
1978-1980	0.157
1981-1983	0.536
1984-1986	1.044
1987-1989	0.625
1990-1992	0.097
1993-1995	0.178
1996-1998	0.037
1999-2001	0.055
2002-2004	0.256
2005-2007	-0.099
2008-2010	1.159
2011-2013	1.376
2014-2016	1.768
2017-2018	1.262

Factor Investing in Liability-Driven Investment Solutions[11]

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- **Factors with a positive long-term premium are natural building blocks for performance-seeking portfolios (PSPs).**
- **To construct a liability-hedging portfolio, one should instead look for the risk factors that explain changes in the value of liabilities.**
- **A factor model suitable for asset-liability management can be used to improve the liability-hedging properties of the PSP.**
- **By choosing a more "liability-friendly" PSP, an investor can enjoy higher average returns without increasing the risk of a drawdown with respect to liabilities.**

A new approach has recently emerged in investment practice known as "factor investing", which recommends that allocation decisions be expressed in terms of risk factors, as opposed to standard asset class decompositions. While the relevance of factor investing is now widely accepted among sophisticated institutional investors, a number of questions remain with respect to the exact role that risk factors are expected to play in an asset-liability management investment process. The main objective of this work is to contribute to the widespread acceptance of factor investing by providing some clarification about the benefits of factor investing within the liability-driven investing paradigm.

Liability-driven investing and factor investing: Two investment paradigms with theoretical foundations

The concept of policy portfolio has long been a cornerstone of institutional money management, where it refers to a portfolio intended to strike a balance between performance and risk relative to a benchmark, the benchmark being the value of liabilities for investors facing commitments. However, modern portfolio theory, pioneered by the work of Harry Markowitz, William F. Sharpe and Robert C. Merton (all awarded the Nobel Prize in economics), shows that the optimal tradeoff between risk and return is in principle obtained by combining a "performance-seeking" building block and a "minimum risk" portfolio, which, in asset-liability management, is the liability hedging portfolio. In the liability-driven investing framework, the relative allocation to these two building blocks depends on outstanding dollar and risk budgets, and also on its periodic revision in reaction to changes in the opportunity set.

In parallel, the recent emergence of factor investing is also connected with advances in financial economics, and more specifically with academic research on asset pricing, notably including the work of Eugene F. Fama (another Nobel Prize winning economist) and Kenneth R. French. Factor models have long been used for the analysis of portfolio risk and performance, but starting with an influential article published in 1993 by Fama and French,[12] factors have gained a new status as explanatory variables for stylized facts that were previously regarded as puzzles. Fama and French proposed to interpret the size and value effects in equities – broadly speaking, small stocks tend to outperform large ones and stocks with high book-to-market ratios tend to outperform those with low ratios – in terms of factor exposures: if the market capitalization and the book-to-market ratio proxy for exposures to undiversifiable risk factors, then small cap stocks and stocks with a small capitalization or a high ratio are more exposed to these risks, which justifies a premium. Although it does not identify the underlying factors, this explanation fits the class of theoretical asset pricing models previously developed by Robert Merton with the Intertemporal Capital Asset Pricing Model (ICAPM) and by Stephen A. Ross with the Arbitrage Pricing Theory (APT). Beyond such risk-based interpretations of patterns related to size, the book-to-market ratio or other characteristics, there is another category of economic rationales according to which these patterns reveal some form of market inefficiency or incomplete rationality of market participants.

In investment practice, the interest in factor investing has been driven by several forces. First, there has been increasing recognition that traditional cap-weighted indexes have a rather bad risk-return profile, which can be improved by investing in stocks endowed with certain observable characteristics, such as low size or high book value relative to capitalization. Second, investors have become increasingly concerned over active management fees and the broad lack of robustness in generating positive and persistent alpha. As a result, they have started to search for added-value investment vehicles with a performance that can be justified by solid economic arguments and does not require complex and expensive processes to select and allocate to securities. Third, the 2008 financial crisis has led to renewed interest in sound risk management practices, so investors are increasingly inclined to ask what risks they face for the returns they earn. These changes have attracted attention to systematic factor investing, now regarded as an approach that blurs the line between passive investing, which involves replicating a cap-weighted index, and active investing, which involves proprietary selection and/or timing skills.

While the relevance of factor investing is now widely established, the discussion around the choice of these factors is ongoing, and a number of questions remain with respect to the exact role they should play. In academia, research has produced many (perhaps too many) candidate "pricing factors," defined as factors that explain differences in expected returns between assets, but not all of them appear to be statistically and economically significant. In investment practice, the notion of factor is more polysemic, and a case can be made that different applications call for different definitions. The rest of this article illustrates the flexibility of the factor investing paradigm by explaining how factors can be used at each stage of the liability-driven investing (LDI) process.

Efficient diversification with factors in the performance-seeking portfolio

In principle, the performance-seeking portfolio (PSP) should be the one that maximizes the Sharpe ratio, regardless of the existence or nature of the investors' liabilities. Unfortunately, this prescription is difficult to implement because the maximum Sharpe ratio portfolio depends on the expected returns of constituents, which are very hard to estimate, and its out-of-sample performance is severely plagued by estimation errors.

As an alternative to statistical analysis, economic models can offer some help to find the composition of this portfolio. The Capital Asset Pricing Model (CAPM), which was introduced by William F. Sharpe and John V. Lintner in 1964 and 1965, identifies it with the "market portfolio," which consists of all assets weighted by their market capitalization and has been traditionally proxied as a broad cap-weighted index of stocks. But the model hinges on rather unrealistic assumptions, including the fact that all investors have identical expectations, which makes it doubtful that a cap-weighted index is the sought-after efficient portfolio, and it is well known that alternative construction methods, as simple as weighting constituents equally, produce higher Sharpe ratios. Thus, in spite of advantages like low turnover and high liquidity, cap-weighted indexes are now regarded as unsatisfactory proxies for efficient benchmarks.

One possible improvement over cap-weighted indexes would be to address their lack of diversification, which results from their excessive concentration in a few large stocks, by changing the weighting scheme, e.g. to equal weighting or variance minimization. A second, non-exclusive option is to revise the model to relax some of its controversial assumptions, as in the ICAPM and APT. A common feature of these models is that they predict that expected returns depend not only on how securities co-move with a single factor, namely the market portfolio as in the original CAPM, but also on their co-movements with multiple factors.

This prediction is an appealing property of these models since it meets the empirical finding that expected returns tend to be associated with multiple, non-redundant attributes. In equity markets, four decades of empirical research have led to a long enumeration of more than 300 candidate characteristics, but only a handful of them are statistically robust and economically plausible. Low size and value were the first to be reported, followed by momentum and low volatility, with low investment and high profitability being the latest to join the short list of

[11] *This research has been supported by Amundi as part of the ETF, Indexing and Smart Beta Investment Strategies research chair at EDHEC-Risk Institute.*
[12] *Fama, E. F. and K. R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33(1): 3–56.*

characteristics with a robust statistical track record and a risk-based or behavioral justification.

By selecting securities with the appropriate characteristics, one can construct portfolios with expected returns above the market without using active management. It is important to note, however, that this profitability usually requires a long investment horizon to be observed, and that in the short run, significant risks of drawdown and underperformance with respect to the cap-weighted index subsist. Examples of such portfolios are given by "investible factor indexes," which provide exposure to selected "factors," understood here as long-only strategies with expected returns above the market or as long-short strategies with positive expected returns. This is apparent from Exhibit 1, where the factor indexes outperform the broad cap-weighted index by 26 to 187 basis points per year between 1972 and 2016, but display maximum relative drawdowns from 17.91% to 38.39%. The second step in the construction of alternative equity indexes would involve improving the diversification of specific risks by deviating from the cap-weighted scheme.

Finally, the investible factors thus constructed can be combined within multi-factor portfolios, the objective of which is to take advantage of multiple factor premia and the relative decorrelation of the factors. One possible objective of such multifactor allocations is to reduce volatility, as shown in Exhibit 1, where the minimum variance portfolio has an annual volatility of 14.59%, less than that of the least volatile constituent (14.71%). Factor combination can also be used to improve the risk-return characteristics of the broad index while managing the relative risk with respect to this benchmark. Thus, a simple equally weighted portfolio of the six constituents outperforms the broad index by 112 basis points per year, with a tracking error of 1.83% and a maximum relative drawdown of 12.08%, both of which are less than those of the individual constituents.

In conclusion, factors are not only useful for designing models to estimate risk and expected return parameters, but they now can also be regarded as building blocks for the construction of a well-rewarded performance-seeking portfolio.

Risk factors and the construction of liability-hedging portfolios

The second building block of an LDI strategy is a liability-hedging portfolio (LHP), whose role is to replicate the performance of liabilities. Because the nature and horizon of the liabilities are specific to each investor, the LHP has to be customized to meet the needs of each investor. Because the objective here is to track the value of liabilities, the relevant factors are those that explain change in this value and are therefore not necessarily those that are relevant for the construction of the PSP. In the typical case where liabilities consist of payments to be made at predetermined dates, their present value is the sum of discounted future cash flows, so the main risk factor is the level of interest rates, and the exposure of liabilities to this factor being measured by their duration. If payments were indexed on realized inflation, the discount rates would be real rates and the risk factor would be the real rate level. In these examples, and more generally when a set of risk factors with large explanatory power is available, a standard replication method is to align the exposures of assets with those of liabilities, thus generalizing the duration hedging strategy to account for the presence of multiple factors. One possible such extension involves hedging not only against unexpected changes in the level of interest rates but also in slope and convexity of the yield curve.

While these methods are commonly employed by defined-benefit pension funds, they could prove equally useful for defined-contribution pension plans and/or retirement products held in individual retirement accounts. In individual money management, a counterpart for the LDI paradigm, which is known as the goal-based investing (GBI) paradigm and the equivalent of the LHP, is a goal-hedging portfolio (GHP). For instance, individuals who save money to generate replacement income in retirement would clearly benefit from having access to an asset or portfolio that pays fixed cash flows at regular intervals in the decumulation phase. However, none of the currently available retirement products or financial securities satisfactorily addresses this need. Standard coupon-paying bonds pay cash flows that are not deferred in the future, and balanced funds and target date funds offer no predictability in terms of the replacement income that they will produce. Deferred annuities would be the ideal risk-free asset, but they suffer from a number of shortcomings including their perceived costliness, lack of transparency and reversibility, and the absence of wealth transfer to heirs. It can be argued that if annuities are useful to hedge against the risk of unexpectedly long life, they are not necessary to generate replacement income for a fixed period of time, e.g. for the life expectancy of an individual at retirement. For this purpose, the risk-free asset would be a forward-starting bond with progressive redemption of principal in such a way that the periodic cash flows are constant. Economists Robert Merton and Arun Muralidhar have called for the creation of such "SeLFIES" (for Standard of Living indexed, Forward-starting, Income-only Securities), and a recent paper co-authored by academics from EDHEC-Risk Institute and Princeton University describes similar "retirement bonds."[13]

In the absence of these bonds in sovereign debt auction programs, one can replicate them with existing fixed-income securities, which provides further scope for the application of factor exposure matching techniques. Exhibit 2 shows summary statistics for two replication strategies, which respectively match the modified duration or the exposure to the level factor calculated from the four-factor model developed by Nelson, Siegel and Svensson. The constituents are "constant-maturity bonds," which are monthly roll-overs of bonds with a constant maturity chosen at a value of one year, two years, etc., until 30 years. At each rebalancing date, – every quarter in this table – the portfolio is invested in the two constituents with the closest durations or exposures to those of the

EXHIBIT 1

Examples of portfolios invested in a single or multiple factor(s) with data from September 1972 to December 2016

The broad cap-weighted index and the six long-only equity indexes are taken from the Scientific Beta database. The six indexes are tilted respectively toward mid-cap stocks, stocks with high book-to-market value, past year winners, low volatility stocks, high profitability stocks and low investment stocks, and they are weighted by capitalization. The last three columns represent portfolios invested in the six factor indexes, respectively an equally weighted portfolio, a minimum volatility portfolio and a minimum tracking error portfolio with respect to the broad index. The tracking error, information ratio and maximum relative drawdown are in relation to the broad index. The last three rows are diversification metrics and display the effective number of constituents as a percentage of the nominal number of constituents, which is 6, and the effective number of correlated bets in volatility or in tracking error.

	Cap-weighted	Mid-Cap	Value	High Mom	Low Vol.	High Prof.	Low Inv.	Equally-weighted	Min Vol.	Min TE
Ann. ret. (%)	10.09	11.96	11.37	10.98	10.37	10.35	11.50	11.21	10.99	10.61
Volatility (%)	16.51	17.85	16.43	17.07	14.71	16.75	15.37	15.82	14.59	16.23
Sharpe ratio	0.34	0.39	0.39	0.35	0.37	0.32	0.43	0.40	0.41	0.35
Max. drawdown (%)	53.78	58.28	61.58	50.44	49.09	52.78	52.57	52.14	43.58	52.84
Tracking error (%)		5.75	5.25	4.05	4.89	3.40	3.71	1.83	4:48	0:98
Info. ratio		0.33	0.24	0.22	0.06	0.08	0.38	0.61	0:20	0:53
Max. rel. drawdown (%)		28.57	32.60	18.71	38.39	17.91	25.64	12.08	41.69	3.08
ENC (%)		16.67	16.67	16.67	16.67	16.67	16.67	100.00	24.49	61.14
ENCB in vol. (%)		16.67	16.67	16.67	16.67	16.67	16.67	99.14	24.49	59.06
ENCB in TE (%)		16.67	16.67	16.67	16.67	16.67	16.67	42.41	21.60	61.75

[13] Martellini, L., V. Milhau and J. Mulvey. 2019. "Flexicure" Retirement Solutions: A Part of the Answer to the Pension Crisis? Journal of Portfolio Management 45(5): 136–151

retirement bond. By testing different accumulation periods, we can see that the GHPs constructed by matching a factor exposure are consistently closer to the bond than a strategy that simply rolls over long-term bonds or short-term money market instruments. Over 11 years of accumulation, the cumulative return of a GHP deviates from that of its benchmark by 0.90% to 5.69%. With long-term bonds, the deviation is from 3.57% to 16.13%, and a cash account, which is often regarded as safe because it never loses money at any horizon, appears highly risky when it comes to securing a certain amount of replacement income: in the best scenario, a cash investor preserves only 68.20% of the initial purchasing power of their savings in terms of replacement income.

The replication exercise can also be performed in decumulation, where the relevant reporting metric is the maximum amount that can be withdrawn every year from the investment portfolio without exhausting savings before the end of the 20-year decumulation period, and without running a final surplus. The results of Martellini and Milhau (2020) again show that the factor exposure replication strategies lead to withdrawal rates that are much closer to that of the retirement bond target compared to the use of a roll-over of bonds or a money market account.[14]

Improving the alignment between the performance-seeking portfolio and liabilities to allocate more to equities

The last stage of the LDI process involves choosing an allocation to the PSP and LHP. Following fund separation theorems, this allocation depends on risk budgets, typically expressed either in terms of a target tracking error or maximum relative drawdown relative to the liabilities. The risk of the LDI strategy depends on the investment policy and the risk of each building block, as well as their correlation. For instance, its tracking error with respect to the liabilities for a given allocation increases with the tracking error of the LHP, but also with that of the PSP, which is not controlled at the portfolio construction stage since fund separation principles recommend that the PSP be designed with no hedging concern in mind. This property has interesting practical consequences because it implies that by decreasing the tracking error of the PSP with respect to the liabilities, an investor can allocate more to this portfolio while staying within the limits of a given risk budget. This leads to an increase in upside potential, unless the performance of the more "liability-friendly" PSP that replaces the original PSP is too inferior.

To construct an equity performance-seeking portfolio with better liability-hedging properties than a broad cap-weighted index – which is often the default option – it is useful to start by measuring the overlap between the PSP and liabilities. This can be done by measuring their respective exposures to a set of risk factors, provided the risk factors have been shown to explain a large fraction of the common time variation of assets and liabilities. We propose to use an eight-factor asset-liability management model with the equity market factor, the long-short size, value and momentum equity factors from Ken French's library, the "betting-against-beta" equity factor, the level

EXHIBIT 2

Simulation of level-matching and duration-matching portfolios in accumulation

Retirement takes place on the first day of the year indicated in the first column. The returns of retirement bonds and the various strategies are simulated from the beginning of accumulation, which is the first day of the month in the second column, until either the retirement date or 1 June 2019, whichever comes first. Simulations are based on the U.S. zero-coupon rates published on the website of the Federal Reserve. The beginning of accumulation is chosen so as to ensure that the maturity of the last replacement income cash flow does not exceed 30 years, since this is the longest maturity of US Treasury bonds.

Retirement year year	Beginning of accumulation	Strategy	Ann. return (%)	Gross relative return (%)	Ann. volatility (%)	Tracking error (%)	Max relative drawdown (%)
2000	Jan. 1989	Ret. bond	10.67	-	10.73	-	-
		GHP Lev.	10.76	100.90	11.50	2.06	3.61
		GHP Dur.	10.78	101.15	11.51	2.08	3.68
		15-year bond	10.98	103.19	12.95	3.90	11.37
		Cash	5.28	57.74	0.21	10.73	52.94
2005	Jan. 1994	Ret. bond	8.69	-	11.51	-	-
		GHP Lev.	8.99	103.15	12.32	1.72	2.39
		GHP Dur.	9.00	103.26	12.40	1.77	2.49
		15-year bond	9.56	109.17	13.58	3.76	8.87
		Cash	3.93	61.12	0.18	11.51	53.25
2010	Jan. 1999	Ret. bond	6.55	-	11.75	-	-
		GHP Lev.	6.97	104.44	12.49	1.45	2.99
		GHP Dur.	6.98	104.55	12.59	1.51	3.10
		15-year bond	6.89	103.57	14.22	4.20	11.56
		Cash	2.91	68.20	0.17	11.75	51.31
2015	Feb. 2004	Ret. bond	7.80	-	12.19	-	-
		GHP Lev.	8.03	102.29	12.84	1.78	6.54
		GHP Dur.	8.12	103.27	13.00	1.84	6.55
		15-year bond	9.06	113.47	14.20	3.53	8.49
		Cash	1.42	51.37	0.14	12.19	53.24
2020	Feb. 2009	Ret. bond	5.27	-	13.36	-	-
		GHP Lev.	5.74	104.71	13.78	1.08	1.39
		GHP Dur.	5.83	105.69	13.90	1.14	1.46
		15-year bond	6.80	116.13	13.13	2.53	5.57
		Cash	0.46	61.69	0.05	13.36	52.05
2025	Jan. 2014	Ret. bond	8.56	-	11.35	-	-
		GHP Lev.	8.81	101.25	11.57	0.68	1.84
		GHP Dur.	8.87	101.55	11.65	0.71	1.86
		15-year bond	7.69	95.72	10.02	1.79	6.94
		Cash	0.79	66.87	0.07	11.35	36.78

[14] *Martellini, L. and V. Milhau. 2020. Factor Investing in Liability-Driven and Goal-Based Investment Solutions. EDHEC-Risk Institute publication.*

of interest rates, the term spread and the credit spread. (The betting-against-beta factor is the excess return of a portfolio of low beta stocks over a portfolio of high beta stocks.) The model captures between 90% and 100% of the variance of equity factor indexes, and 96.6% of that of liabilities. Liabilities are mostly exposed to term structure factors, as expected, but equity indexes are also exposed to these factors, sometimes significantly in the statistical sense, and not all of them have the same exposure, which suggests that they have heterogeneous hedging abilities. For instance, we find that the low volatility index has the most negative exposure to the level factor, thus making it the most "bond-like."

With the factor model at hand, a variety of new PSPs can be constructed using different weighting methods, including minimizing the distance between the exposures of the equity portfolio and those of liabilities, minimizing the systematic tracking error with respect to the liability portfolio (defined as the part of the tracking error that arises from factor exposures), or by maximizing the "effective number of bets" (ENB), i.e. by maximising diversification across the eight factors. Variants of these weighting schemes are additionally obtained by constraining the tracking error with respect to the broad index to be less than a cap, say 2% per year. As is clear from Exhibit 3, the relative risk of an equity portfolio is reduced by replacing the broad index with a PSP constructed from equity factor indexes, especially when the constituents are minimum variance as opposed to cap-weighted portfolios. For instance, the maximum relative drawdowns of alternative PSPs range from 55.94% to 73.63%, vs. 77.38% for the broad index, and with the provision of the unconstrained minimum distance portfolio of cap-weighted indexes, these PSPs also have lower tracking errors by 24 to 204 basis points per year. In addition, they outperform the broad index because the expected long-term outperformance of long-only factors over the equity market materialized in this sample period.

Thus, starting from a reference strategy invested in the broad index and the perfect LHP with respective weights of 40% and 60%, one can allocate more than 40% to each alternative PSP while keeping the maximum relative drawdown of the strategy unchanged. As a result, each strategy using an alternative PSP outperforms the reference strategy by an amount that depends both on the increase in allocation and in the gain in average return within the PSP. For instance, the strategy in which the PSP is the portfolio that minimizes the systematic tracking error earns 9.94% per year, vs. 9.72% for the one that uses the broad index. The annual gain may seem to be modest, but after 45 years, it translates into a gain of 9.81% in funding ratio. With minimum variance versions of these factor portfolios, the gain in funding ratio over the sample period rises to 117.51%, thanks to the higher annual return of the PSP.

In conclusion, while factor investing and liability-driven investing relate to two separate strands of the academic literature, a strong case can be made for combining these approaches. Each of the three steps of a liability-driven investing process, namely the construction of a wellrewarded performance-seeking portfolio, the construction of a safe liability-hedging portfolio, and an efficient allocation to these building blocks, can be better addressed by taking a factor perspective. Our article can be regarded as a first step toward the introduction of a comprehensive investment framework blending liability-driven investing and factor investing. •

The research from which this article was drawn was produced as part of the Amundi ETF, Indexing and Smart Beta Investment Strategies research chair at EDHEC-Risk Institute.

EXHIBIT 3

Liability-driven investing strategies with matched relative maximum drawdown; data from September 1971 to December 2016

Minimum distance, minimum systematic tracking error and maximum ENB portfolios are invested in the six equity factor indexes, and some of them are subject to a 2% tracking error constraint per year with respect to the broad index. The allocation to the PSP is calculated so as to match the maximum relative drawdown of the reference strategy over the sample period, the reference strategy being the one invested in the broad index and the LHP. Liabilities are represented by a 10-year constant-maturity bond. The gain in funding ratio with respect to the reference strategy is calculated as [1+r2]/[1+r1] – 1, where r1 and r2 are the respective cumulative returns of the reference strategy and the alternative one.

Performance-seeking portfolio	Equ.-broad	Min distance		Min systematic tracking error		Max ENB	
Target TE w.r.t. Equ.-broad (%)	-	None	2	None	2	None	2
Cap-weighted indexes PSP							
Annual return (%)	10.15	11.84	11.17	10.47	10.86	10.47	10.69
Tracking error (%)	19.16	20.59	18.76	17.32	18.19	17.32	18.92
Max relative drawdown (%)	77.38	67.90	68.34	68.24	70.51	68.24	73.63
LDI Strategy							
Allocation to PSP (%)	40.00	50.87	51.32	50.40	47.72	50.40	44.09
Annual return (%)	9.72	10.92	10.43	9.94	10.13	9.94	10.02
Volatility (%)	9.46	10.43	9.86	9.50	9.53	9.50	9.53
Cumulative relative return (%)	64.80	169.99	121.27	80.97	95.58	80.97	86.58
Gain in funding ratio w.r.t. reference (%)		63.83	34.27	9.81	18.68	9.81	13.22
Tracking error (%)	7.51	10.22	9.47	8.62	8.55	8.62	8.20
Information ratio	0.16	0.24	0.20	0.17	0.19	0.17	0.18
Max relative drawdown (%)	40.79	40.79	40.79	40.79	40.79	40.79	40.79
Minimum variance indexes PSP							
Annual return (%)	10.15	12.97	12.90	12.65	12.90	12.65	12.90
Tracking error (%)	19.16	18.02	17.94	16.12	17.94	16.12	17.94
Max relative drawdown	77.38	63.44	57.57	55.94	57.57	55.94	57.57
LDI Strategy							
Allocation to PSP (%)	40.00	55.96	64.47	66.75	64.47	66.75	64.47
Annual return (%)	9.72	11.55	11.81	11.61	11.81	11.61	11.81
Volatility (%)	9.46	9.72	10.54	9.83	10.54	9.83	10.54
Cumulative relative return (%)	64.80	249.75	288.60	258.45	288.60	258.45	288.60
Gain in funding ratio w.r.t. reference (%)		112.23	135.80	117.51	135.80	117.51	135.80
Tracking error (%)	7.51	9.91	11.43	10.67	11.43	10.67	11.43
Information ratio	0.16	0.31	0.29	0.29	0.29	0.29	0.29
Max relative drawdown (%)	40.79	40.79	40.79	40.79	40.79	40.79	40.79

Robust and Interpretable Liquidity Proxies for Market and Funding Liquidity

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- **We introduce two interpretable liquidity measures that can be obtained from publicly available prices, and correlate well with liquidity measures that require transaction-level information.**
- **Our measures have distinct reversion speeds, which sort and mirror the different reversion speeds of the input liquidity proxies.**
- **We interpret our measures as relating to market and funding liquidity, and we justify this interpretation.**
- **The sensitivity of assets to liquidity can be easily determined by linear regression.**

Introduction

The importance of liquidity is widely recognized by both academics and practitioners. Unfortunately, being a latent quantity, liquidity is not easy to measure (and sometimes even to define). Most proxies of liquidity require the use of microstructural, transaction-level data. This type of information is often proprietary, and, when publicly available, it often refers to the most liquid securities – for which liquidity impairment is arguably less of a problem.

This paper therefore introduces a statistical method to estimate two measures of liquidity (which we call 'market' and 'funding') with the following positive features:

1. they can be calculated using publicly available prices or yields;
2. they are interpretable;
3. they correlate well with measures that require transaction-level data (such as the measures recently introduced by Hu, Wang and Pan, 2015; Konstantinovsky, Ng and Phelps, 2016; and Adrian, Etula and Muir, 2015);
4. they can be easily translated (e.g. via regression) into the sensitivity to market and fining liquidity of individual securities.

The intuition behind our approach is very simple. First, we identify a number of proxies whose behavior is affected, possibly together with other factors, by changes in funding liquidity. We construct their covariance matrix, and carry out (sparse and traditional) Principal Component Analysis. By retaining only the first (two) principal components, we attempt to "push" the non-liquidity confounding factors (such as credit) into the higher components (which we neglect). Of course, we have to justify our claim that most of the non-liquidity factors have indeed been pushed into the higher principal components that we neglect.

When we carry out this procedure, we identify two clear measures of liquidity, which we characterize as "market" and "funding" liquidity components. We also find that these two measures of liquidity naturally sort the input proxy variables into two distinct sets of proxies, with very different and very clearly identifiable reversion speeds, which are neatly inherited by the measures we build.

Market and Funding Liquidity

The literature on liquidity is vast (albeit strongly skewed toward equities). For a useful recent review see Adler (2012). The contributions most closely linked to our work are Brunnermeier and Pedersen (2009), whose results are discussed later in this section, Hu, Pang and Wang (2012), Adrian, Etula and Muir (2014) and Acharya and Pedersen (2005), whose results are compared with ours in detail in Section 5.

It is widely recognized that there are (at least) two aspects of liquidity, often referred to as market liquidity and funding liquidity, or "normal" and "crisis" liquidity. See Danielsson, Song Shin and Zigrand (2009) for a theoretical treatment and International Monetary Fund (2015) and Bank for International Settlements (2016) for an institutional perspective. Brunnermeier and Pedersen (2009), Danielsson, Song Shin and Zigrand (2009) and Boudt, Paulus and Rosenthal (2013), among others, have investigated the effects of these different liquidity regimes on asset prices. Despite the wide acceptance of the existence of two "types of" liquidity, there is no consensus about how these two regimes or modes should be defined, let alone identified.

In our approach we do not posit a priori that there should exist one or two "types of" liquidity. Rather, two different liquidity measures naturally arise from the procedure we describe below, and we argue that these two statistically obtained measures can be clearly distinguished from one another (on the basis of their different reversion speeds). More precisely, we estimate our liquidity measures by adapting an approach first introduced by Ludvigson and Ng (2009) in the context of excess returns in US Treasuries.

We adapt and modify their procedure as follows. We first choose n financial time series, yt, each of length N , which we have reason to believe are strongly affected by liquidity (see Section 2.1 for a justification of our choices of variables). Next, as in Korajczyk and Sadka (2008), we standardize the proxies by subtracting their mean and dividing by their standard deviation. We then create the covariance matrix, Σ_{lev}, among their levels and we orthogonalize it:

$$\Sigma_{lev} = V \Lambda V^T, \qquad (1)$$

where V is the $n{\times}n$ orthogonal matrix of eigenvectors, and Λ the $n{\times}n$ diagonal matrix of eigenvalues. With the eigenvectors thus obtained we construct the $N \times n$ matrix of principal components, PC_t:

$$\underbrace{PC_{t:}}_{[N\times n]} = \underbrace{y_t}_{[N\times n]} \underbrace{V}_{[n\times n]}. \qquad (2)$$

We retain $k < n$ of these principal components, which we interpret as liquidity measures and analyze in Section 5.

Choice of and Justification for the Component Proxies

Which proxies should reasonably be considered representative of liquidity (i.e., how should we choose the n financial time series, yt)?

First of all, microstructural considerations (see, e.g., Easley et al., 2011, Foucault, Pagano and Roell, 2013, and Brunnermeier and Pedersen, 2013) and analysis of macro-financial data (see, e.g., Fontaine and Garcia, 2015) suggest that liquidity should be inversely related to volatility. We therefore include volatility-related quantities in our set of input liquidity proxies.

During periods of severe market distress there is a well-documented tendency for investors to try to shift their portfolios toward safe-haven assets such as Treasuries (this is the deleveraging phase in our model). This can only be achieved by selling riskier assets. Concentrated selling pressure in these riskier assets creates problems for the associated market makers, leading to wider spreads and reduced liquidity. Therefore, some indicators of preference for safe-haven assets should be included in our list of liquidity proxies. Among these, the on-the-run/off-the-run spread (difference in yields between the on-the-run and off-the-run 10-year Treasury, discussed at length in Fontaine and Garcia, 2015) is probably the ultimate safe-haven indicator, and we therefore include it in our set of proxies.

The same reorientation of portfolios away from risky assets also occurs, albeit over longer time frames, when economic fundamentals are perceived to have worsened or to be worsening. If the assets that investors want to dispose of are illiquid to start with (such as emerging-market bonds or high-yield credit issues), this systematic selling pressure can also create problems for market makers, and hence reduce the liquidity of the assets. Therefore, we include quantities such as emerging-market and high-yield bond spreads among our proxies.

Finally, a reduction in liquidity can hinder the access to funding for the pseudo-arbitrageurs and the immediacy providers (market makers); indeed, Fontaine and Garcia (2015) find that liquidity is linked to factors measuring monetary conditions in the economy and in the banking system in particular. We therefore include quantities such as the TED and LIBOR/OIS spreads as plausible indicators of (funding) liquidity.

The chosen proxies are all strongly correlated (see Table 1) and each one is a very plausible proxy for liquidity. Indeed, casual inspection of their time series, as in Fig. 1, would make it very difficult to attribute a *priori* any deep meaning to the differences between any two proxies – at first blush, any or all of them could be taken as a defensible liquidity proxy. In reality, we show in what follows that this superficial similarity hides subtle but important differences.

In order to quantitatively differentiate between the proxies, we examined their mean-reverting properties. The reversion speeds and half-lives of the nine proxies are shown in Table 2, sorted by increasing reversion speed.

As this table shows, we find a very wide range of mean reversion speeds, with half-lives ranging from two months to almost a year and a half. Since the speed of mean reversion is linked to the time over which liquidity is typically restored to the market after a shock, this is a very important quantity. We will revisit their behavior in what follows, but for the moment we note that the two fastest mean-reverting proxies (LOIS and TED spreads) are both closely linked to the funding of financial intermediaries (dealer/brokers – the pseudo-arbitrageurs in our model).

Apart from the ability to provide a useful interpretation, this grouping of the standardized proxies on the basis of mean reversion is also quantitatively interesting, because, as we shall see, it is closely mirrored in the different reversion speeds of our two liquidity measures.

Features of Our Liquidity Measures

The orthogonalization of the covariance matrix of the nine chosen proxies (see Equation 1) produces the first two eigenvectors shown in Fig. 2. The first principal component displays the usual almost constant-loading pattern found in most principal component analyses. The second principal component is made up of positive loadings for LOIS and TED (the two fastest mean-reverting proxies, again confirming that these two variables "work together") and of negative loadings for OnOff, EM and HY (all associated with the slowest reversion speeds). It is very interesting to note how the differences in reversion speeds (which the PCA "knows nothing about") are exactly picked up in the construction of the loadings for the second principal component. A sparse PCA (not reported in detail for the sake of brevity) confirms this grouping.

The time series of the first two principal components, $PC1_t$ and $PC2_t$, obtained from the first two columns of the quantities PC_t in Equation 2 are shown in Fig. 3. These quantities are key to our analysis because they are our measures of liquidity.

The incremental and cumulative percentage of the total variance explained by the first n principal components ($n \leq 1 \leq 9$) is shown in Table 3: we note that the first two principal components explain close to 90% of the total variance of the nine proxies, suggesting that little is lost by neglecting the higher eigenvectors.

Finally, as for the reversion-speed properties of the first two principal components, we note that the first is much more slowly mean-reverting than the second (with half-lives of 1.27 and 0.39 years, respectively, nicely mirroring the reversion speeds in Table 2). This important aspect is discussed at length in Section 4, where we offer an interpretation of the two liquidity measures that we have introduced in this section.

Interpretation of the Liquidity Measures

The market/funding interpretability of our liquidity measures is an important feature of our approach. So far we have established some empirical facts, namely

1. that the original liquidity proxies have a wide range of reversion speeds, with funding-liquidity proxies the fastest mean-reverting,
2. that our two liquidity measures display different reversion speeds,
3. that the reversion speeds of our liquidity measures closely match the fastest and slowest reversion speeds of the input proxies, and
4. that the fastest-reverting proxies are associated with funding liquidity.

Therefore, we make the inference that we can associate one liquidity measure with funding liquidity and the other with market liquidity. In this section we therefore explore in detail whether this inference is warranted by undertaking a

TABLE 1

The correlation between the nine proxies described in the text

	VIX	3m10y	1m1y	AAA	EM	HY	LOIS	TED	OnOff
VIX	1								
3m10y	0.75	1							
1m1y	0.65	0.68	1						
AAA	0.81	0.70	0.70	1					
EM	0.84	0.72	0.44	0.87	1				
HY	0.87	0.79	0.55	0.89	0.97	1			
LOI	0.76	0.59	0.78	0.85	0.71	0.73	1		
TED	0.62	0.49	0.86	0.72	0.48	0.53	0.92	1	
OnOff	0.78	0.90	0.63	0.78	0.80	0.84	0.64	0.49	1

TABLE 2

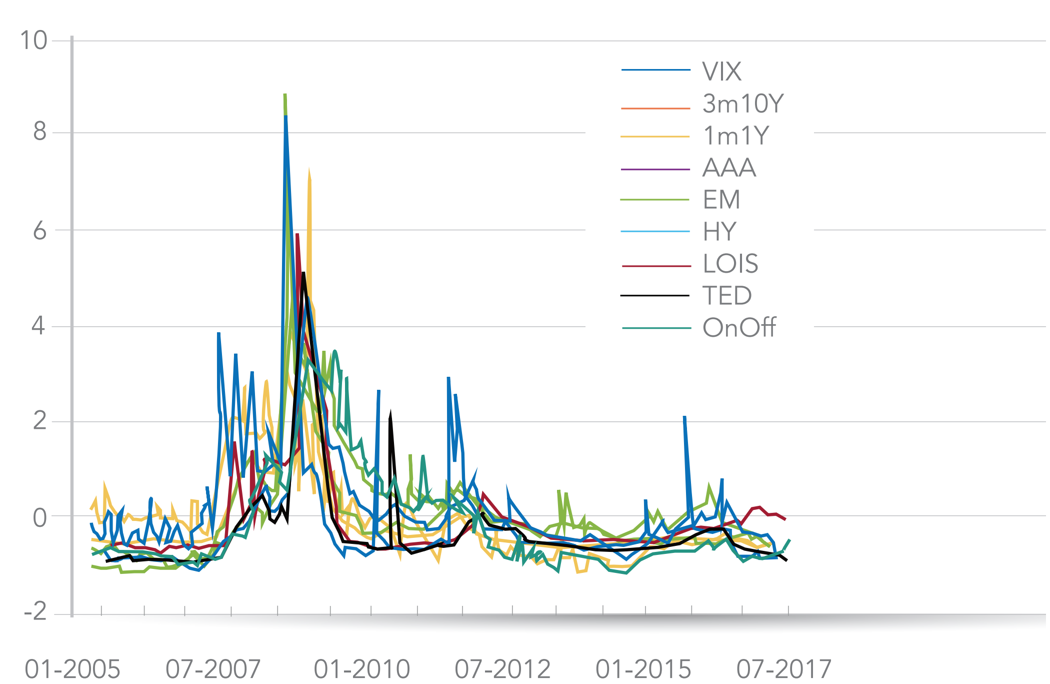
The reversion speeds (yrs^{-1}) for the various proxies with their one-standard-deviation error, and the associated half-lives

The reversion speeds were obtained by regressing $x_{t+\tau}$ against x_t, for $\tau = 1/12$ (years), and obtaining the reversion speed, κ, from the slope (β) of the regression $x_{t+\tau} = \alpha + \beta x_t + E_t$ with $\beta = \exp(-\kappa\tau)$ and $\alpha = \theta(1 - \exp(-\kappa\tau))$.

	Reversion Speed (yrs−1)	Half-life (months)
On/Off spread	0.53 ± 0.30	15.65
EM	0.57 ± 0.30	14.60
HY	0.57 ± 0.31	14.53
AAA	1.15 ± 0.43	7.21
3*m* × 10Y volatility	1.52 ± 0.49	5.47
1*m* × 1Y volatility	2.49 ± 0.60	3.33
VIX	2.74 ± 0.62	3.04
LOIS	3.49 ± 0.68	2.38
TED	3.91 ± 0.71	2.13

FIGURE 1

The time series of the nine liquidity proxies, each standardized by its own standard deviation



detailed event analysis.

To this effect, we carry out a careful comparison of the salient features of the two principal components (such as peaks, trends, levels, etc.) against major events in the period under study which can be plausibly assumed, or are known, to have had an impact on liquidity, and on the availability of funding. In Figures 4 and 5 we present times series for the first two principal components, punctuated by the salient events of the period under consideration. (A description of the abbreviations and a short narrative is provided in Appendix.)

First of all, we note that all the major crisis events *(LEH + MER, WAMU , WB, DJIA– 778, etc.)* have left a clear signature in the time series of both principal components as a sharp increase. Next, we note that when the second principal component peaks, the first also peaks, but the converse is not true. For instance, Figure 5 clearly shows that there is a single major peak in the time series of the second principal component, located in the immediate aftermath of the Lehman default, and two minor peaks on Aug. 20, 2007, and Aug. 12, 2007. These peaks are all also present in the time series of the first principal component, as shown in Figure 4. This latter series, however, also displays pronounced peaks on March 5, 2009, Oct. 4, 2011, Nov. 23, 2011, Aug. 24 , 2015, and Feb. 11 , 2016, but these peaks are not present in the time series of the second principal component. Other minor peaks are visible for the first principal components and, again, these are missing or very muted in the time series of the second principal component.

This is again consistent with the interpretation of the second principal component as an indicator of the deterioration in liquidity associated with the severest dislocations (funding liquidity shock in our model), and that of the first principal component as a reflection of all sources of liquidity deterioration.

Another feature is worth discussing. The point labeled *"Crisis END"* ushers in the onset of a very clear decaying exponential-like reduction in the first principal component *after the end of the crisis.*[15] The same end-of-crisis marker corresponds to the end of the fall for the second principal component. The most significant changes associated with this marker are therefore after the end-of-crisis point for the first principal component, and before it for the second. This is consistent with our interpretation of the two principal components as market-plus-funding and funding-only liquidity indicators: as market and economic conditions progressively heal, the first principal component signals a continuous and slow improvement in market liquidity; once the severe distress is over, however, the second principal component does not signal any further improvement in the funding liquidity, despite the fact that the world economy is far from healed.

Finally, we note that changes in equity market excess returns[16] are strongly (negatively) correlated with the first principal component ($\rho = -60\%$), but virtually uncorrelated with changes in the second ($\rho = 1\%$). This fits in well with a model like that of Brunnermeier and Pedersen (2008), who point out that market liquidity should co-move with the market factor, and with the findings in Fontaine and Garcia (2012), who find that liquidity covaries positively with changes in aggregate uncertainty, which they also proxy by the volatility of the S&P500 index.[17]

In sum: the event analysis presented in this section points to the following conclusions:

- the largest deterioration of liquidity is due to the withdrawal of funding;
- more mundane occurrences of (market) liquidity impairment occur more frequently;
- shocks to market and funding liquidity are reversed with very different reversion speeds;
- the reversion speeds of our two measures closely mirror the reversion speeds of market and liquidity shocks.

FIGURE 2

The loadings of the nine volatility proxies used to obtain the first two eigenvectors (first two columns of matrix V in Equation 1)

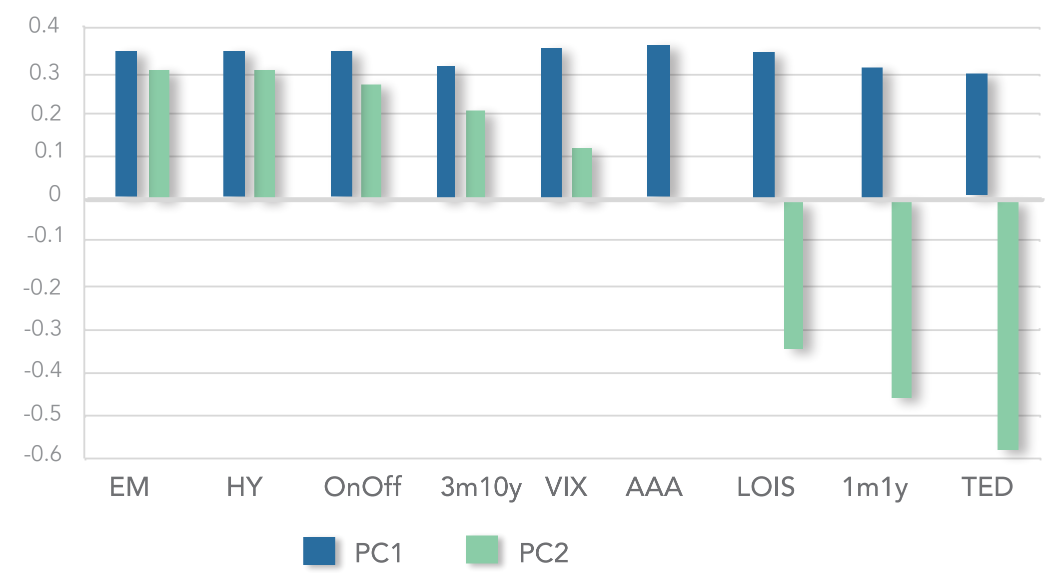


FIGURE 3

The time series of the first two principal components, $PC1_t$ and $PC2_t$, obtained from the first two columns of the quantities PC_t in Equation (2)

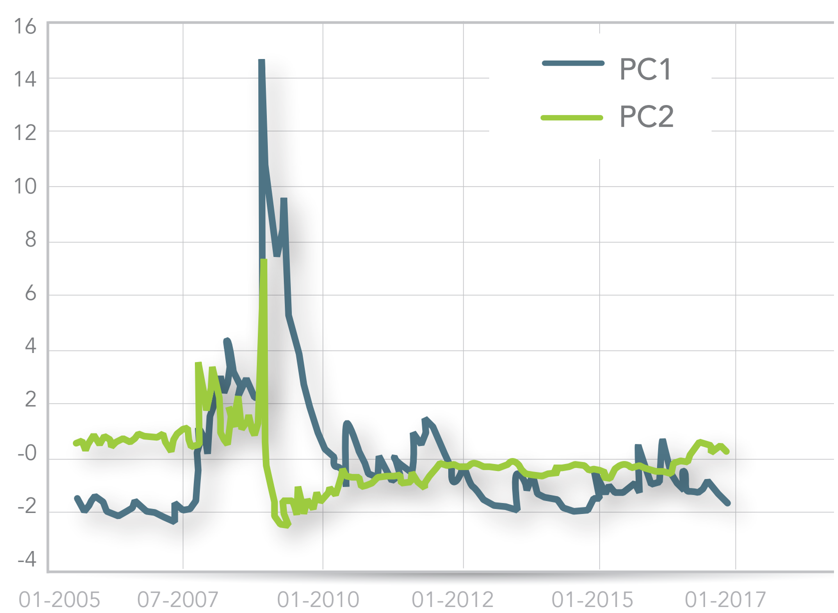


TABLE 3

The incremental and cumulative fraction of variance explained by the various Principal Components (percentage points)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Incremental	76.0	12.3	6.1	2.1	1.3	1.1	0.5	0.4	0.2
Cumulative	76.0	88.3	94.4	96.5	97.8	98.9	99.4	99.8	100.0

[15] *By 9 March 2009, the Dow had fallen to 6440, exceeding the pace of the market's fall during the Great Depression and reaching a level which the index had last seen in 1996. On 10 March 2009, a rally began which took the Dow up to 8500 by 6 May 2009. By 9 May, financial stocks had rallied more than 150% in just over two months. The start of March has therefore been taken as the end point for the crisis.*
[16] *We have taken returns on the S&P500 as a proxy for equity market returns.*
[17] *Fontaine and Garcia (2012) look at implied rather than realized volatility. The two quantities are highly correlated.*

FIGURE 4

Time series of the first principal component, with selected salient liquidity-related market events as markers

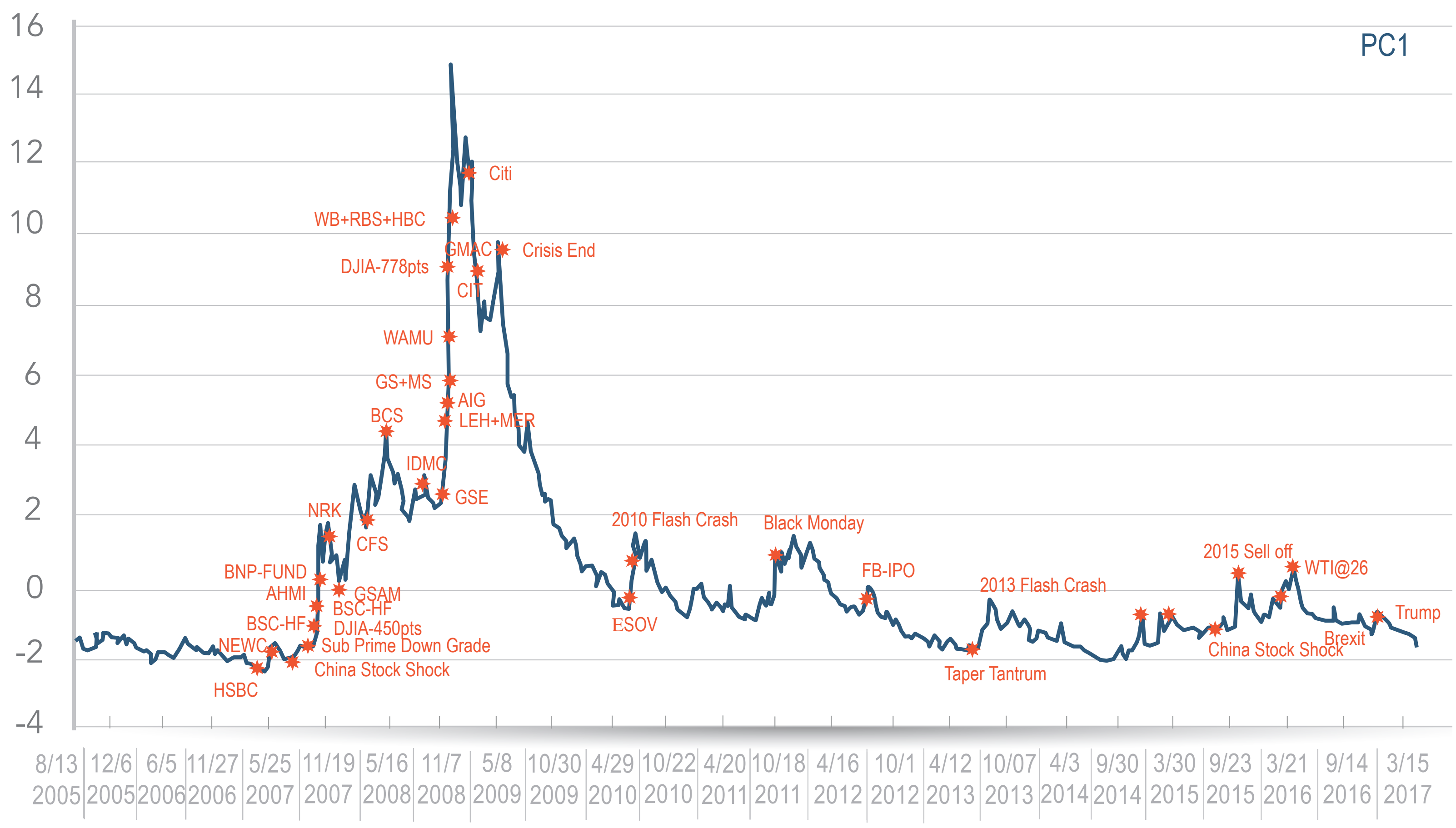


FIGURE 5

Time series of the second principal component, with selected salient liquidity-related market events as markers

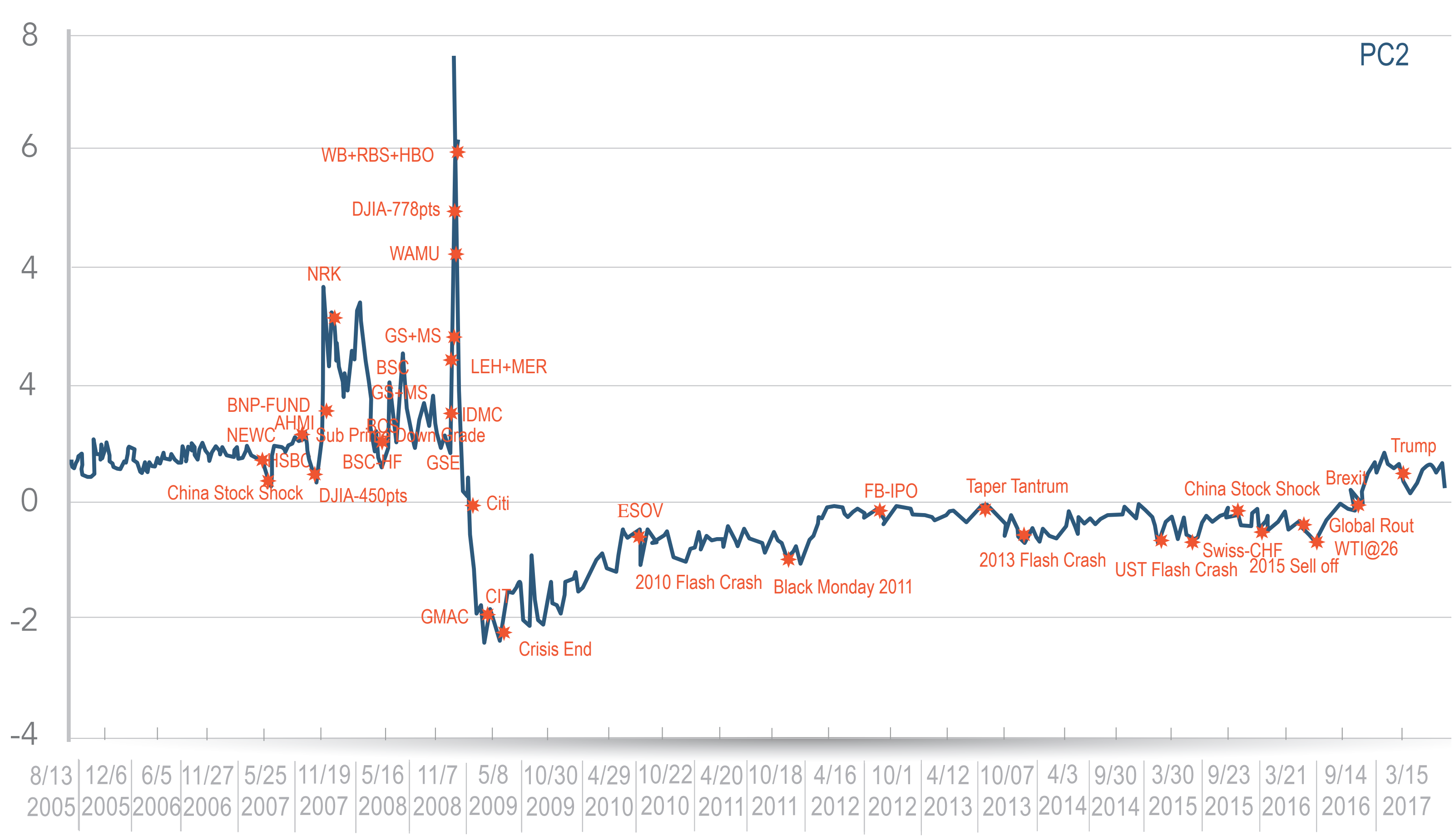


TABLE 4

The coefficients in the regressions
$LCS_t = \alpha_1^{LCS} + \beta_1^{LCS} PC1_t + E_t^{LCS,1}$, $Noise_t = \alpha_2^{LCS} + \beta_2^{LVS} PC2_t + E^{LCS,2}$, $BDL_t = \alpha_2^{BDL} + \beta_2^{BDL} PC2t + E_t^{BDL,2}$ **and** $PSt = \alpha_2^{PS} + \beta_2^{PS} PC2_t + E_t^{DL,2}$ **for the two principal components, with the t-statistics in square brackets. The fifth and ninth columns column show the R2**

	α^{Noise}	$\beta^{Noise}{}_1$	$\beta^{Noise}{}_2$	R^2	α^{LCS}	$\beta^{LCS}{}_1$	$\beta^{LCS}{}_2$	R^2
PC1	2.94 [122.7]	1.07 [128.0]	-	0.88	0.60 [51.2]	0.09 [20.6]	-	0.78
PC2	3.16 [47.0]	-	-0.22 [3.8]	0.01	0.62 [25.2]	-	-0.05 [2.0]	0.03
	α^{BDL}	β^{BDL}	β^{BDL}_2	R^2	$\alpha^{P\&S}$	$\beta^{P\&S}_1$	$\beta^{P\&S}_2$	R^2
PC1	0.29 [32.1]	0.01 [1.84]	-	0.02	0.42 [1.15]	-0.84 [1.0]	-	0.0.1
PC2	0.30 [41.8]	-	0.07 [9.9]	0.42	0.41 [1.13]	-	0.56 [0.48]	0.00

Comparison With Related Work

We have discussed at length the salient features of our liquidity measures. In the literature, a number of liquidity proxies have been recently proposed. How do they compare with our measures?

Our first observation is that the liquidity measures which have been recently introduced all require the availability of granular or aggregate transaction-level data (bid-offer spreads, volume information, broker-dealer inventories, etc.). While obtaining some of the transactional data may be relatively simple for equities, it can pose serious problems for other asset classes. In this section we therefore compare our measure(s) of liquidity, which rely only on readily available price information, with the most popular measures introduced in the recent literature, all of which use additional information other than past prices.

These measures are:

- "liquidity as noise" by Hu, Wang and Pan (2015)[19], Noise hereafter;
- the Barclays Liquidity Credit Score by Konstantinovsky, Ng and Phelps (2016), LCS hereafter;
- the broker-dealer leverage measure by Adrian, Etula and Muir (2015), BDL hereafter; and
- Pastor and Staumbaugh's (2003) aggregate liquidity measure, P&S hereafter.

Noise is built from the pricing errors in fitting to individual Treasuries using a popular (Nelson and Siegel, 1987) fitting methodology. The intuition is that, in normal market conditions, the small price deviations from fair value (as ascertained by the Nelson-Siegel model) are arbitraged away by speculators. As market liquidity deteriorates, in the model by Hu, Wang and Pan (2015) speculators have less available capital to 'correct' the price deviations, which therefore become a signal of market liquidity. If our interpretation is correct, the *Noise* measure can therefore be expected to be more strongly correlated with our first measure, which captures both types of liquidity impairments.

The *LCS* measure is built using Barclays dealer quote data[20], and is a direct trading cost expressed as a percentage of the bond price. It is bond-specific and updated daily. By the way it is constructed, it should reflect changes in both funding and market liquidity, and should therefore display the strongest correlation with our first liquidity measure.

Adrian and Etula (2015) argue that liquidity is linked to the pro-cyclical broker-dealer balance sheet adjustments. They therefore construct a measure of leverage by defining broker-dealer leverage,
BDL, as

$$BDL = \frac{\text{Total Financial Assets}}{\text{Total Financial Assets} - \text{Total Liabilities}}. \quad (3)$$

We independently constructed a dealer leverage factor using data from the Financial and Operational Combined Uniform Single Report (FOCUS). While the firms selected by Adrian and Etula (2015) were limited to primary dealers, with our data we were able to access the raw total assets and equity for over 400 US-registered broker-dealers at a monthly frequency, thereby creating a more comprehensive measure. By the way it has been constructed, we expect the BDL measure to more closely track our second principal component, which we have associated with deterioration in funding liquidity, than the first.

Finally, Pastor and Staumbaugh's Aggregate Liquidity measure is extracted from volume-related stock return reversals cross-sectionally. Using data between 1966 and 1999 the authors found that on average 7.5% annual return can be attributed cross-sectionally to a market-wide liquidity. Sharp declines in their Aggregate Liquidity measure coincide with market downturns and flights to quality.

To explore whether our liquidity measures behave as expected, we regress the four indicators of liquidity mentioned above, $LiqInd^k$, against our first and second principal components:

$$LiqInd_t^k = \alpha_1^k + \beta_1^k PC1_t + \varepsilon_t^{k,1} \quad (4)$$

$$LiqInd_t = \alpha_2 + \beta_2^k PC2_t + \varepsilon_t \quad (5)$$

with the index k identifying the four liquidity measures found in the recent literature (*k = 1: Noise, k = 2: LCS, k = 3: BDL, k = 4: P &S indicator*).

19 *We thank Dr. Pan for providing the Noise data series.*
20 *We thank Konstantinovsky, Ng and Phelps for making the BLC data available.*

Our predictions are well borne out by the results of the regressions, shown in Table 4. In particular:

1. the *Noise* and *LCS* liquidity indicators are strongly correlated with our first liquidity measure, and weakly with the second.
2. the *BDL* indicator is correlated with our second liquidity measure, and weakly with the first. It is also poorly correlated with *Noise* and *LCS* ($\rho_{BDL,LCS}$ = 0.12, $\rho_{BDL,\ Noise}$ = 24.7, respectively).
3. plotting the broker-dealer leverage *BDL* measure against *Noise* and *LCS* clearly shows that *BDL* picks up very different aspects of liquidity: in the initial phases of the crisis it remains elevated, suggesting, in line with Adrian and Etula (2015), strongly pro-cyclical behaviour. See Figure 6 and Table 5, which show the correlation between the BDL, LCS, NOISE, PC1 and PC2 liquidity measures.

Neither of our principal components shows any correlation with Pastor and Staumbaugh's liquidity measure, but this measure shows little or no correlation with any of the other liquidity measures discussed in this section.

Overall, the interpretation of the first principal component as a mixture of market and funding liquidity and of the second principal component as a proxy for funding liquidity has found further corroboration from the analysis presented in this section. Given the way we have defined liquidity (market or funding) as the cost of a buy-and-sell "round trip," it is also very comforting to note the close link between our first liquidity measure and the LCS measure (that is directly built using bid-offer information). This is particularly noteworthy because we do not use bid-offer or any transaction-level information in our construction.

Conclusions

This article introduces two novel measures of liquidity, linked to what we define as "market" and "funding" liquidity. Our measures can be constructed using publicly available prices and yields, yet are highly correlated with recently proposed measures that require information such as bid-offer spreads, broker-dealer leverage or the output of a Treasury fitting model.

We claim that simplicity of construction is not the only (or indeed the main) positive feature of our measures. We have made the case that our liquidity measures (i) pick up different aspects of liquidity, namely market and funding liquidity (which we have defined); (ii) are less likely to be affected by non-liquidity-related confounding factors (such as credit); and (iii) are interpretable.

Our two liquidity measures differ by their mean-reversion properties, highlighting fast and slow mean-reverting "types of" liquidity shocks. This different behavior is clearly mirrored in the mean-reverting behavior of the underlying proxies. To our knowledge these differences in speeds of liquidity restoration have not been commented on before, but we think that they are highly meaningful.

Appendix - 'Dictionary' of Event Acronyms

Date *Events* Description

02/01/2007 *HSBC* HSBC announces losses linked to U.S. subprime mortgages.

02/27/2007 *China Stock Shock* The SSE Composite Index of the Shanghai Stock Exchange tumbles 9% from unexpected selloffs, the largest drop in 10 years, triggering major losses in worldwide stock markets.

04/02/2007 *NEWC* Subprime mortgage lender New Century Financial (NEWC) files for bankruptcy-court protection.

06/01/2007 *SubPrimeDownGrade* Standard & Poor's and Moody's Investors Service downgrade over 100 bonds backed by second-lien subprime mortgages.

06/07/2007 *BSC – HF* Two Bear Stearns (BSC)-run hedge funds with large holdings of subprime mortgages face significant losses and are forced to dump assets. The trouble spreads to major

FIGURE 6

BDL, Noise and LCS liquidity measures after normalization. Note the markedly different behavior of the BDL measure (linked to the pro-cyclical behavior of broker-dealers) before the severest parts of the crisis (left panel) and the time series of our second liquidity measure and of the BDL measure (left panel)

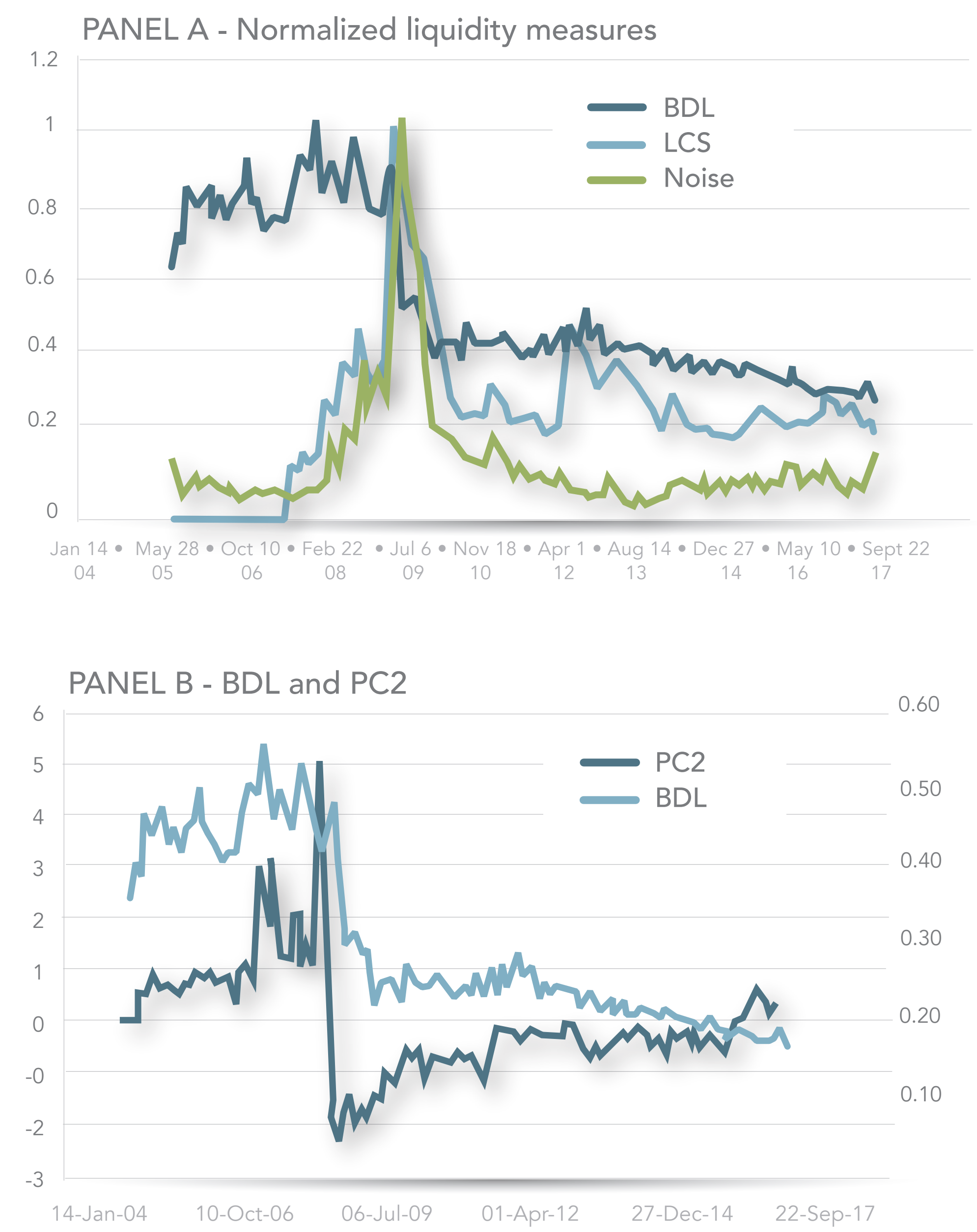


TABLE 5

Correlation between BDL, Noise, LCS and our two liquidity measures

	PC1	Noise	LCS	PC2	BDL
PC1	1				
Noise	0.89	1			
LCS	0.88	0.83	1		
PC2	-0.02	-0.019	-0.17	1	
BDL	0.35	0.24	0.13	0.63	1

Wall Street firms such as Merrill Lynch, JPMorgan Chase, Citigroup and Goldman Sachs that had loaned the firms money.

07/26/2007 *DJIA* – 450pts Worries that problems in housing and credit markets would dent the broader economy sent stocks tumbling, pulling the Dow Jones industrial average down more than 400 points.

07/31/2007 *BSC* – HF Bear Stearns (BSC) liquidatestwo hedge funds that invested in various types of mortgage-backed securities.

08/06/2007 *AHMI* American Home Mortgage Investment (AHMI), which specializes in adjustable-rate mortgages, files for bankruptcy protection.

08/09/2007 *BNP* – Fund BNP Paribas freezes three of its funds, indicating that they have no way of valuing the complex collateralized debt obligations (CDOs), or packages of sub-prime loans.

09/14/2007 *NRK* Depositors withdraw £1 billion from Northern Rock (NRK) in what is the biggest run on a British bank for more than a century.

10/15/2007 *GSAM* Sub-prime mortgage market disruption spills over to U.S. equity strategies, causing 28% loss to Goldman Sachs quant funds (GSAM).

01/11/2008 *CFC* Bank of America, the biggest U.S. bank by market value, agrees to buy Countrywide Financial (CFC) for about $4 billion.

03/14/2008 *BSC* Bear Stearns (BSC) is bought by JPMorgan Chase.

07/11/2008 *IDMC* Federal regulators seize IndyMac Federal Bank (IDMC) after it becomes the largest regulated thrift to fail.

09/08/2008 *GSE* Mortgage giants Fannie Mae and Freddie Mac (GSEs) are taken over by the government.

09/15/2008 *LEH + MER* Lehman (LEH) files for bankruptcy and thousands of its employees lose their jobs. This is the largest bankruptcy filing in the history of the U.S., with $639 billion in debt. Bank of America agrees to a $50 billion rescue package for Merrill Lynch (MER). Shares in European stock exchanges plunge. The FTSE 100 closes almost 4% down at 5,202.4, a 210 point drop. The Dow Jones Industrial average plunges 504 points to close at 10,917.51.

09/16/2008 *AIG* American International Group (AIG), the world's largest insurer, accepts an $85 billion federal bailout that gives the government a 79.9% stake in the company.

09/22/2008 *GS + MS* Goldman Sachs (GS) and Morgan Stanley (MS), the last two independent investment banks, become bank holding companies subject to greater regulation by the Federal Reserve.

09/25/2008 *WAMU* Federal regulators close Washington Mutual Bank (WAMU) and its branches and assets are sold to JPMorgan Chase in the biggest U.S. bank failure in history.

09/29/2008 *DJIA* – 778pts Congress rejects a $700 billion Wall Street financial rescue package, known as the Troubled Asset Relief Program or TARP, sending the Dow Jones industrial average down 778 points, its worst single drop ever.

10/03/2008 *WB + RBS + HBOS* Congress passes a revised version of TARP and President George W. Bush signs it. Wells Fargo & Co. agrees to buy Wachovia (WB) for about $14.8 billion. The U.K. government ends up owning the majority share in the Royal Bank of Scotland (RBS) and over a 40% share in Lloyds and HBOS in a bailout.

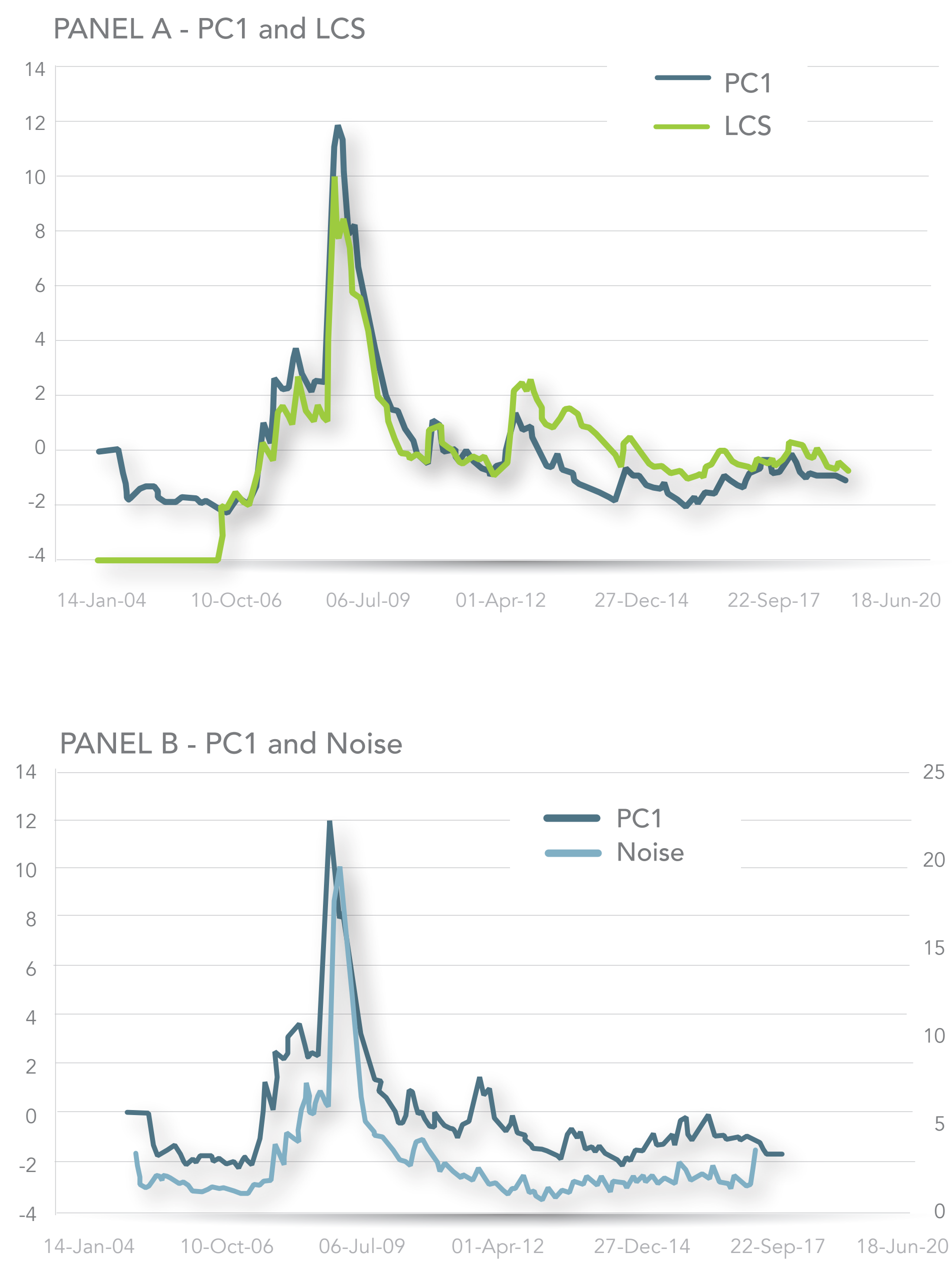
11/24/2008 *Citi* The Treasury Department, Federal Reserve and Federal Deposit Insurance Corp. agree to rescue Citigroup with a package of guarantees, funding access, and capital.

12/22/2008 *CIT* The Federal Reserve Board, quoting "unusual and exigent circumstances," approves the application of CIT Group Inc., an $81 billion financing company, to become a bank holding company.

12/29/2008 *GMAC* The U.S. Treasury unveils a $6 billion

FIGURE 7

The time series of our first liquidity measure and of the LCS measure (left panel), and Noise measure (right panel)



bailout for GMAC, the car-loan arm of General Motors.
03/09/2009 *Crisis – End* By March 9, 2009, the Dow had fallen to 6440, exceeding the pace of the market's fall during the Great Depression and a level which the index had last seen in 1996. On March 10, 2009, a rally began which took the Dow up to 8500 by May 6, 2009. Financial stocks rose more than 150% during this rally, in just over two months.
04/27/2010 *EUR SOV* European Sovereign Debt Crisis. Standard & Poor's downgrades Greece's sovereign credit rating to junk four days after the activation of a EUR 45 billion EU–IMF bailout, triggering the decline of stock markets worldwide and of the euro's value, and exacerbating a European sovereign debt crisis.
05/06/2010 *2010FlashCrash* The Dow Jones Industrial Average suffers its worst intra-day point loss, dropping nearly 1000 points before partially recovering.
08/08/2011 *BlackMonday DJIA* -17% (-2180 pts) following the Friday night credit rating downgrade by Standard and Poor's of U.S. sovereign debt from AAA, or "risk free," to AA-plus. It was the first time in history the United States had been downgraded.
05/18/2012 *FB – IPO* The largest tech IPO (Facebook) in history ($16 billion), with stock opening at $42.05 on Friday, quickly fell to its issue price of $38 after a delay due to a glitch in Nasdaq OMX's IPO software. It closed at $38.23 on Friday. On Monday it closed in New York down 11% at $34.03.
05/22/2013 *TaperTantrum* U.S. bond crash (10-year Treasury yield reaches 2.71% from 1.64%). Fed chairman Bernanke suggests the Fed may start tapering QE sooner if warranted by the data.
08/23/2013 *2013 FlashCrash* The NASDAQ closed from 12:14 pm to 3:25 pm EDT. One of the computer servers at the NYSE couldn't communicate with a NASDAQ server that fed it stock price data.
10/15/2014 *USTFlashCrash* Treasury 10-year suddenly dropped 37 basis points. High Frequency Traders (HFTs) and Principal Trading Firms (PTFs) blamed.
01/15/2015 *Swiss – CHF* SNB removed 1.2 CHF/EUR cap, resulting in a 30% appreciation in CHF.
06/12/2015 *ChinaStockShock 2015–16* Chinese stock market crash. In January 2016, the Chinese stock market experiences a steep sell-off which sets off a global rout.
08/24/2015 *2015SellOff* The Dow fell 1089 points to 15,370.33 as soon as the market opened. It was a 16% drop from its May 19 all-time high of 18,312.39. It quickly recovered, and closed just 533 points down. This followed a 531 point drop the previous Friday. Both were caused by worries about slower economic growth in China, and uncertainty over its yuan devaluation.
01/07/2016 *GlobalRout* On both Jan. 4 and Jan. 7, 2016, the Chinese stock market fell by about 7% sending stocks tumbling globally. From Jan. 4 to Jan. 15, it fell 18% and the Dow Jones industrial average was down 8.2%.
02/11/2016 *WTI@26* WTI trades at $26 per barrel, down from $115 in 2014.
06/24/2016 *Brexit* Panic linked to the U.K.'s Brexit referendum wipes $2 trillion off world markets.
FTSE100 3.2% loss after intraday 9% plunge, Pound dropped to a 30-year low.
11/08/2016 *Trump* A surprising Trump victory saw the overnight Futures on the Standard & Poor's 500-stock index initially plunge 5% but it recouped nearly all its losses when stocks started trading in the U.S. The major market indicators ended the day up more than 1%.

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Cross-Sectional Momentum in the U.S. Sovereign Bond Market[21]

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- **Cross-sectional reversal strategies are also profitable, but only when adjusted for duration.**
- **Security-level analysis is indispensable to obtain meaningful results.**
- **Cross-sectional momentum and reversal strategies can be implemented in a long-only fashion.**

Momentum strategies have been found to be profitable in a wide number of asset classes. In equity markets, a well-known early example of academic research in this area is a paper by Jegadeesh and Titman (1993), who found a statistically significant positive performance over the period 1965–1989 for dollar-neutral cross-sectional momentum strategies that had purchased best performing U.S. stocks over the previous three to 12 months, sold the losers and held the position for three to 12 months. Cross-sectional momentum strategies have also been studied in the U.S. equity market by Moskowitz and Grinblatt (1999), and in European stock markets by Rouwenhorst (1998). Similar cross-sectional strategies were later found to be profitable in currencies (e.g., Menkhoff et al., 2012). All such strategies consist of buying (selling) securities that recently outperformed (underperformed) their peers over the past three to 12 months.[22]

In a recent paper (Rebonato, Maeso, and Martellini, 2019), we complement this strand of the literature by presenting a systematic empirical investigation of the profitability of cross-sectional momentum and reversal strategies in U.S. Treasuries, using more than 40 years of daily data at the individual security level. Looking at the security level is very important, because studies that instead employ "synthetic" zero-coupon bonds can be vitiated by the well-known serial autocorrelation of pricing errors, which can masquerade as a momentum effect.[23] To our knowledge, no empirical study of momentum in Treasuries has analyzed the problem at this level of granularity. In what follows, we summarize the results obtained for cross-sectional momentum and reversal strategies for different sets of lookback and holding periods in long-short and also long-only settings.

Dataset

The data used for the study are the daily close-of-business day prices for 1,562 U.S. Treasury coupon bonds over the period Dec. 27, 1973, to June 29, 2018.[24] At each date t, we only considered bonds with a time-to-maturity higher than or equal to two years and lower than or equal to 15 years. Finally, we computed bond total return price series by assuming that each coupon paid by a given bond would be reinvested in the same bond. Exhibit 1 reports the summary statistics of our Treasury bond sample, which contains 46,578 monthly return observations.

Long-Short Cross-Sectional Momentum Strategies

For the long-short framework, we apply the following empirical methodology, suggested by Lewellen (2002), to build a zero-cost cross-sectional momentum strategy:

1. We fix a lookback period of L months and a holding (investment) period of H months. In order to limit the possibility of data mining, we use identical lookback and holding (investment) periods. We consider four possible values for the couple (L,H): (3,3), (6,6), (9,9) and (12,12).
2. At end of month date t, we consider all the N_t bonds that *(i)* are in the universe at date t, *(ii)* were in the universe at date $t - L$ *and (iii)* that will be in the universe at date $t + H$.
3. At date t, we compute for each bond i its relative L-month past excess return with respect to the market: $(r^L_{i,t} - r^L_{m,t})$. $r^L_{i,t}$ is the bond i's L-month past performance, and $r^L_{m,t}$ is the market's L-month past performance.[25]
4. At date t, we assign to each bond i the weight: $w_{i,t} = \frac{1}{N_t}(r_{i,t} - r_{m,t})$.

   Note that we have: $\sum_{i=1}^{N_t} w_{i,t} = 0.$
5. Finally, we normalize the weights so as to have a cross-sectional zero-cost momentum portfolio, i.e. 1$ long and 1$ short at the beginning of the investment period:

$$w^{norm}_{i,t} = \frac{w_{i,t}}{\sum_{i=1}^{N_t} w^+_{i,t}} \text{ where } w^+_{i,t} = w_{i,t} \text{ if } w_{i,t} > 0 \text{ and } w^+_{i,t} = 0 \text{ otherwise.}$$

[21] This research has been supported by Amundi as part of the ETF, Indexing and Smart Beta Investment Strategies research chair at EDHEC-Risk Institute.
[22] One can also define time-series momentum, namely the strategy of looking at the past performance of each security over the last three to 12-months, and of buying (selling) those with positive (negative) past performance over a certain investment period.
[23] For instance, the widely used zero-coupon bond prices by Gürkaynak et al. (2007) are obtained by fitting the Nelson and Siegel (1987) model to the market prices of coupon-bearing bonds. As the authors recognize, these fitted prices suffer from serially correlated pricing errors.
[24] All these bonds are non-callable, non-puttable and non-inflation-linked. We thank ICE for providing us with the dataset used for our empirical analysis. We excluded from the dataset prices of individual bonds that were deemed to be erroneous based on setting a threshold in standard deviations for price changes, and then excluding those bonds whose price move exceeded the threshold when the other bonds in the universe did not show a similar move for that same day.
[25] The market is proxied by an equal-weight portfolio of the N_t bonds.

We also implement a cross-sectional duration-adjusted momentum strategy by following the same protocol as above but by duration-adjusting the notional of the short and long positions. Duration adjustment is achieved by dividing the returns of each bond by their duration. The duration-adjusted market return is the cross-sectional average of the duration-adjusted bond returns. Duration adjustment – which does not imply duration neutralization – is performed so as to achieve an approximate risk parity (volatility parity) among the various constituent bonds. We normalize the weights to have a cross-sectional zero-cost momentum portfolio that is 1$ long and 1$ short at the beginning of the investment period. We emphasize that the zero-cost cross-sectional (duration-adjusted or not) reversal strategies are defined as the symmetric opposite of the zero-cost cross-sectional (duration adjusted or not) momentum strategies.

The descriptive statistics for the cross-sectional duration-adjusted strategies are shown in Exhibit 2. The cross-sectional momentum non-duration-adjusted strategies are unprofitable with annualized mean returns ranging from -0.1% for a 12-month holding period to 0.2% for a nine-month holding period. The t-statistic points to non-significant results. The picture changes radically for cross-sectional strategies when we introduce duration-adjustment: after adjusting for duration (i.e., roughly normalizing with respect to volatility), we find significant profitability for all the reversal strategies, but also significant results for three out of the four lookback/investment periods (six, nine and 12 months): for instance the annualized mean return of the six-, nine- and 12-month duration-adjusted reversal strategies respectively are 0.9%, 1.1% and 1.3%.

One may wonder why duration adjustment brings about such a marked improvement in the cross-sectional strategies. To understand the origin of this improvement in performance, it should be remembered first that, by adjusting duration, in order to establish winners and losers we divide both the market and the security returns by their durations. Since yield curve moves are dominated by quasi-parallel shifts in yields, without duration adjustment winners and losers tend to be found at either end of the maturity spectrum (the long end if rates have fallen, and the short end if they have risen). If the Treasury returns were only due to parallel moves in the yield curves, dividing by the duration would approximately equalize the returns from bonds of different maturities, and there would be no reason to find winners and losers preferentially at either end of the maturity spectrum.

Indeed, we do find that after duration adjustment, the polarization of winners and losers at either end of the yield curve is less pronounced, and intermediate maturity bonds are now often picked as winners. However, there still remains a strong predominance of long- or short-maturity bonds among the winners and losers. Since we have neutralized against parallel movements in the yield curve, this can only mean that the profitability of the duration-adjusted strategy is closely linked to changes in the slope of the yield curve. It is well known, in turn, that the yield curve slope (closely related to the second principal component of yield changes) is strongly mean-reverting (see Diebold and Rudebusch, 2013). The success of the cross-sectional duration-adjusted reversion strategy therefore appears to be linked to the mean-reverting properties of the yield curve slope. More precisely, by determining the winners and losers after dividing by duration, weights are created that can exploit the mean-reverting properties of the slope. Indeed, we find that a cross-sectional reversion strategy now becomes very profitable.

EXHIBIT 1

Individual Bond Database Descriptive Statistics

Sample Period	**December 1973 - June 2018**
Bond-Month Observations	46578
Monthly Return-Mean (%)	0.52
Monthly Return-Median (%)	0.38
Monthly Return-First Quartile (%)	-0.26
Monthly Return-Third Quartile (%)	1.22
Duration-Mean (years)	4.32
Duration-Median (years)	3.92
Duration-First Quartile (years)	2.77
Duration-Third Quartile (years)	5.58
Time to Maturity-Mean (years)	5.45
Time to Maturity-Median (years)	4.54
Time to Maturity-First Quartile (years)	3.09
Time to Maturity-Third Quartile (years)	6.92

This figure contains the main descriptive statistics of the bond database.

EXHIBIT 2

Descriptive Statistics of Long-Short Cross-Sectional Momentum Strategies

This figure reports the main descriptive statistics (annualized mean total return, annualized volatility and Sharpe ratio) of the long-short cross-sectional momentum strategies without duration-adjustment (Panel A) and with duration-adjustment (Panel B). The row labelled 't-stat (Newey-West)' reports the t-statistic for the rejection of the hypothesis that the mean in the first row is zero.

Panel A: Non-Duration-Adjusted

Look-back and holding periods (months)	**3M**	**6M**	**9M**	**12M**
Mean return (annualized)	0.0%	0.1%	0.2%	-0.1%
Volatility (annualized)	4.1%	4.1%	4.2%	4.3%
Sharpe ratio	0.0	0.03	0.04	-0.01
t-stat (Newey-West)	-0.02	0.37	0.46	-0.15

Panel B: Duration-Adjusted

Look-back and holding periods (months)	**3M**	**6M**	**9M**	**12M**
Mean return (annualized)	-0.5%	-0.9%	-1.1%	-1.3%
Volatility (annualized)	3.8%	3.8%	3.9%	3.8%
Sharpe ratio	-0.14	-0.23	-0.29	-0.34
t-stat (Newey-West)	-1.16	-2.21	-3.13	-4.11

Long-Only Cross-Sectional Momentum Portfolios

From the perspective of important classes of institutional investors with investment constraints, long-only portfolios are particularly relevant. We therefore present the results for three long-only strategies in this section:

1. Giving equal positive weights to all the bonds;
2. Giving duration-adjusted positive weights to the past losers; and
3. Giving duration-adjusted positive weights to the past winners.

For the long-only framework, we compare the returns from giving each bond in the universe an equal duration-adjusted notional with the returns from giving equal duration-adjusted weights to the previous period's winners and losers. More precisely, we build a yearly-rebalanced long-only duration-adjusted winner portfolio as follows:

1. At inception date, we compute for each bond its duration-adjusted one-year past total return with respect to the duration-adjusted one-year past total return of the market.
2. We only keep bonds for which the previous quantity is positive in the winner portfolio and we define intermediary bond weights in that portfolio as: $w_{i,t} = \frac{1}{N_t^+}(r_{i,t} - r_{m,t})$.
3. We finally normalize the weights such that their sum is equal to one.
4. We keep the portfolio buy-and-hold until the next rebalancing date.
5. At each rebalancing date we rebalance the portfolio by following steps 1, 2 and 3.

The procedure to build the yearly-rebalanced long-only loser portfolio is analogous. The results are shown in Exhibit 3 and in tabular form in Exhibit 4, where it is found that the reversal ("losers") portfolio outperforms the momentum ("winners") portfolio and the market portfolio in terms of mean return (7.7% vs. 6.4% and 7.1%).

CONCLUSION

We have shown that long-short duration-adjusted cross-sectional reversal strategies are significantly profitable over an extended range of lags (six to 12) and illustrate a possible application of this result in a long-only framework. We link the profitability to two concomitant factors: (i) the ability of the duration-adjustment procedure to single out winners and losers by their exposure to slope changes, and ii) the degree of mean-reversion of the slope. The reader will find additional results in Rebonato, Maeso, and Martellini (2019) on momentum in U.S. Treasuries especially on (i) the profitability of time-series momentum strategies and (ii) the existence of a universal exact identity relationship between the expected returns of two different time-series momentum strategies and the expected return of a cross-sectional momentum strategy in a stylized setting.

EXHIBIT 3

Descriptive Statistics of Long-Only Cross-Sectional Duration-Adjusted Momentum and Reversal Portfolios

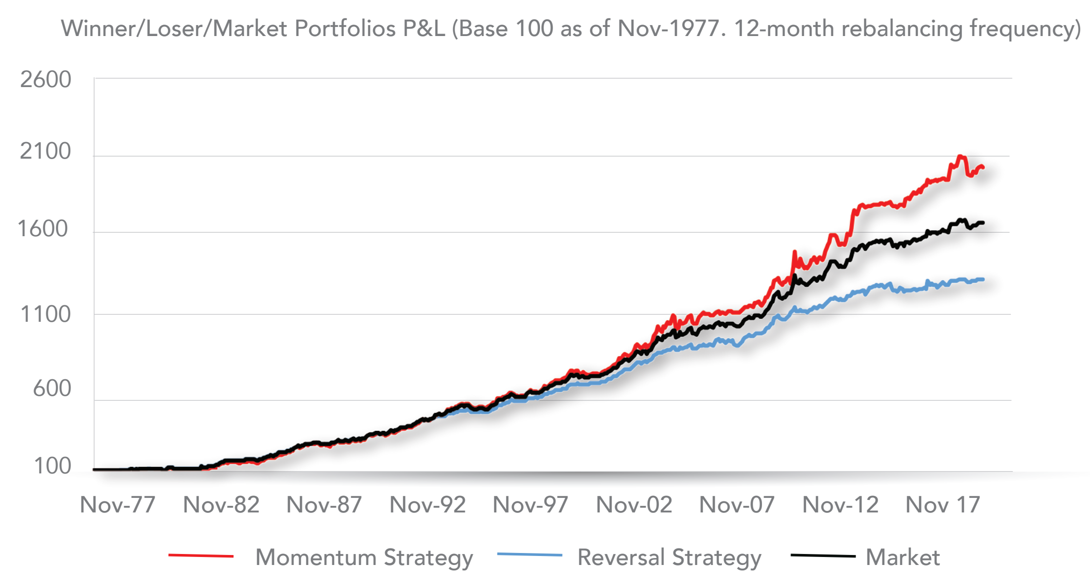
This figure reports the main descriptive statistics (annualized mean total return, annualized volatility and Sharpe ratio) of the long-only cross-sectional duration-adjusted momentum and reversal portfolios. The row labeled "t-stat (mean TR = null)" reports the t-statistic for the rejection of the hypothesis that the mean in the first row is zero.

	Winner Ptf	Loser Ptf	Market
Mean TR	6.4%	7.7%	7.1%
Vol	4.4%	7.6%	5.9%
SR	0.43	0.42	0.43
t-stat (mean TR = null)	6.4551	9.3443	7.6128

EXHIBIT 4

Cumulative Returns for Cross-Sectional Duration-Adjusted Momentum and Reversal Portfolios

This figure displays the cumulative returns from giving duration-adjusted weights to all bonds (curve labeled "Market"); duration-adjusted weights to past winners (curve labeled "Momentum Strategy"); and duration-adjusted weights to past losers (curve labeled "Reversal Strategy").



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