Deutsche Bank

Global Markets Research

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Signal Processing

The long and the short of it

Research Summary
In this report we use a unique database of securities lending data to construct new alpha factors. We show that these factors can add value on top of existing quant strategies, even after implementation costs.

Capturing the alpha in stock lending data

New alpha factors
In this report we use the DataExplorers securities lending database to develop new alpha signals based on stock lending and borrowing data. We show that we can combine these signals into a composite factor that works well in forecasting month-ahead stock returns.

There is no free lunch
However, we find that some of the apparent alpha in the factor is eroded by the cost of trading the short side of the signal, which tends to be skewed towards hard to borrow names. We develop a way to adjust the factor scores for shorting costs, which helps steer the factor towards less costly names on the short side. This allows us to implement the factor in a real-world, long-short portfolio with more confidence.

Long-only opportunities
Of course, for long-only investors borrowing costs are not an issue. We show that long-only investors can actually generate significant alpha by underweighting hard to borrow stocks.

The real cost of factors
We use cost of borrow data to study the true cost of trading the short side of common quant factors. This information can be useful for investors who want to account for this (often overlooked) cost in model building or portfolio construction.

Source: Getty Images

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DataExplorers Disclaimer

A letter to our readers

The long and the short of it

We pick up where we left off last year: looking for new databases and new alpha signals

Welcome to the first *Signal Processing* of 2011. Last year we spent a lot of time looking for new data sources and alpha signals.[1] We believe finding new factors is one of the most important ways to react to the current quant environment, which is characterized by diminishing returns to the traditional alpha signals like value, momentum, and earnings quality. With this in mind, we kick off 2011 where we left off in 2010 – with another new database.

In this report, we turn our attention to the securities lending market. Regular readers of our *Academic Insights* research series would have noticed quite a few academic papers on the subject of short interest recently. Many of these studies find evidence that heavily shorted stocks tend to underperform lightly shorted stocks in the future. However, finding a good data source for securities lending data has always been a challenge due to the fragmented nature of the market and the fact that these transactions occur over-the-counter.

A new source for securities lending data

DataExplorers is a data vendor that collects securities lending data

For this study, we use data provided by a data vendor called DataExplorers, who have constructed a large database of securities lending data by collecting information from a wide range of participants in the stock lending market, including beneficial owners (i.e. lenders), buy side investors (i.e. borrowers), and intermediaries (i.e. prime brokers). An interesting feature of the database is that subscribers who want to use the data must also submit their own lending or borrowing data back into the data pool.

According to DataExplorers, their database now encompasses around 90% of the securities lending market, covering some 220,000 individual securities and over US$ 12 trillion in capitalization.

There's alpha on the table, but can we harvest it?

We find that factors constructed from securities lending data can add alpha, even after the sometimes high implementation costs

In our analysis we find that factors constructed from the securities lending market do have predictive power in forecasting month-ahead stock returns. However, implementation of these strategies requires careful thought, because the cost of shorting stocks that rank poorly on these metrics can be prohibitive. As a result, a particular focus of our research is to determine how we can build signals from stock lending data that can realistically be implemented by a long-short quantitative investor (or indeed a long-only investor, where things are actually simpler because borrowing costs are not an issue).

As always, if you have any questions or comments please let us know.

Regards,

Yin, Rocky, Miguel, Javed, and John
Deutsche Bank North American Equity Quantitative Strategy

[1] For a complete compilation of all our research from last year, see: Luo, Y., R. Cahan, M. Avarez, J. Jussa, and Z. Chen, 2010, "DB Quant Handbook: 2010, year of the tiger", *Deutsche Bank Quantitative Strategy*, 10 December 2010. This book is over 700 pages and is available only in hard copy. We have a limited number of copies left; if you would like one please contact us and we would be happy to send a copy.

Stock screens

Picking stocks using securities lending data

The three screens below contain our best long, underweight, and short ideas respectively based on the Deutsche Bank Security Lending (DBSL) factor described in this research. Note that the top underweight ideas are different from the top short ideas. This is because investors who short need to take the cost of shorting into account when using the DBSL factor. For this reason we used a cost-adjusted version of the factor (which we call DBSLX) for the short picks, but an unadjusted version (DBSL) for the long and underweight ideas (since these investors do not face shorting costs). The complete details of these factors are discussed in detail in the remainder of this report.

Long or overweight ideas

Figure 1: Top 10 long or overweight ideas, S&P 500 universe

Ticker	Name	GICS Sector	DBSL Score
AIZ	ASSURANT INC	Financials	7.8
ETR	ENTERGY CORP	Utilities	7.7
CNP	CENTERPOINT ENERGY INC	Utilities	7.6
CVH	COVENTRY HEALTH CARE INC	Health Care	7.5
CSC	COMPUTER SCIENCES CORP	Information Technology	7.1
FRX	FOREST LABORATORIES -CL A	Health Care	7.1
AEP	AMERICAN ELECTRIC POWER CO	Utilities	6.8
ADBE	ADOBE SYSTEMS INC	Information Technology	6.6
HUM	HUMANA INC	Health Care	6.4
MCK	MCKESSON CORP	Health Care	6.4

Note: A higher DBSL score indicates a more attractive long or overweight position. The DBSL factor is a composite factor based on securities lending data, which is designed to forecast stock returns for the coming month. For the complete details of the factor, please see the remainder of this report.
Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Underweight ideas

Figure 2: Top 10 underweight ideas, S&P 500 universe

Ticker	Name	GICS Sector	DBSL Score
AN	AUTONATION INC	Consumer Discretionary	-6.3
FSLR	FIRST SOLAR INC	Information Technology	-6.2
CTL	CENTURYLINK INC	Telecommunication Services	-6.1
SHLD	SEARS HOLDINGS CORP	Consumer Discretionary	-5.8
FII	FEDERATED INVESTORS INC	Financials	-5.8
DO	DIAMOND OFFSHRE DRILLING INC	Energy	-5.3
V	VISA INC	Information Technology	-4.8
VMC	VULCAN MATERIALS CO	Materials	-4.4
FAST	FASTENAL CO	Industrials	-4.4
MOLX	MOLEX INC	Information Technology	-4.3

Note: A larger negative DBSL score indicates a more attractive underweight position. The DBSL factor is a composite factor based on securities lending data, which is designed to forecast stock returns for the coming month. For the complete details of the factor, please see the remainder of this report.
Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Short ideas

Figure 3: Top 10 short ideas, S&P 500 universe

Ticker	Name	GICS Sector	DBSLX Score
CTL	CENTURYLINK INC	Telecommunication Services	-6.2
DO	DIAMOND OFFSHRE DRILLING INC	Energy	-5.5
V	VISA INC	Information Technology	-5.0
VMC	VULCAN MATERIALS CO	Materials	-4.6
FAST	FASTENAL CO	Industrials	-4.5
MOLX	MOLEX INC	Information Technology	-4.4
NKE	NIKE INC	Consumer Discretionary	-4.3
MCHP	MICROCHIP TECHNOLOGY INC	Information Technology	-4.2
WPO	WASHINGTON POST -CL B	Consumer Discretionary	-4.1
HRB	BLOCK H & R INC	Consumer Discretionary	-4.0

Note: A larger negative DBSLX score indicates a more attractive short position. The DBSLX is a composite factor based on securities lending data, which is designed to forecast stock returns for the coming month. For this screen, the factor is adjusted for the cost of borrowing each stock. For the complete details of the factor, please see the remainder of this report.
Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Setting the scene

Introducing the DataExplorers database

The securities lending market has long been a mystery to many investors due to its lack of transparency

Historically, the biggest challenge in modeling the securities lending market has been getting good quality data. The securities lending market is not an organized exchange per se, rather it is a collection of interconnected participants – including beneficial owners, intermediaries, and borrowers – who borrow and lend securities for a wide variety of reasons. The opacity of this network, and the fact that the transactions occur over-the-counter, has historically made data collection difficult.

However, this is starting to change. A data provider called DataExplorers is trying to fill in the gaps by collecting and cleaning securities lending data. Founded in 2002, the company now believes they cover around 90% of the global securities lending market, drawing data from a wide range of market participants including 120 global custodian banks, over 100 institutional buy-side firms, and 9 of the top 10 prime brokers.[2] A unique feature of DataExplorers' approach is that subscribers to the dataset are themselves required to submit their own securities lending data back into the data pool. As a result, as usage of the data grows, the coverage also expands.

However, a data provider called DataExplorers has been building a comprehensive database of securities lending data

Metrics

The DataExplorers database includes a wide range of securities lending metrics which are collected at a daily frequency. Broadly speaking, the data capture four key aspects of the securities lending market:

- **Demand** metrics measure the borrowing demand in each security, i.e. how many shares are currently on loan to borrowers, and how has this changed over time.
- **Supply** metrics capture the available inventory, or shares available to borrow, for a given security. In other words, these metrics capture the number of shares that beneficial owners (e.g. pension funds, mutual funds, etc.) have available to lend out.
- **Utilization** metrics combine supply and demand, by measuring the percent of available inventory that is currently on loan.
- **Costs** are measured by a variety of metrics that capture the cost of borrowing a particular security. This is a particularly important category for quant investors, who tend to follow long-short market neutral strategies and hence need to short frequently.

Needless to say, these broad classifications gloss over a number of intricacies in the database. For readers interested in getting a more detailed description of the database, DataExplorers provides a Frequently Asked Questions document that is a good starting point for digging deeper into the data.[3] Additionally, we include a full list of available data items in the Appendix of this report, and also elaborate on some of the more important items as we analyze and backtest them in the rest of this study.

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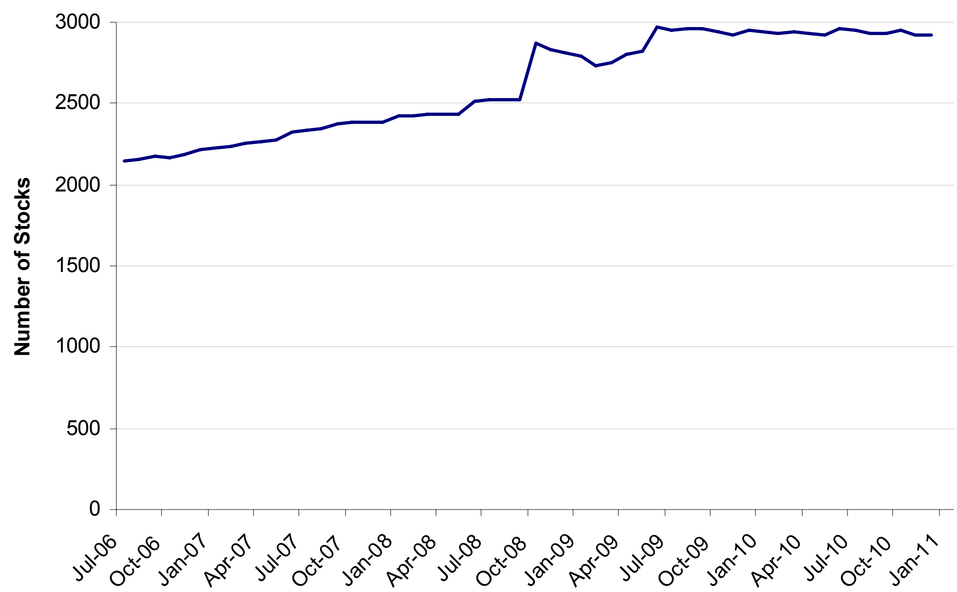
[2] DataExplorers, 2011, "Strategic Update Q1 2011: Securities Finance", January 2011
[3] DataExplorers, 2010, "Buy side data feed FAQ", May 2010

The DataExplorers database covers around 90% of the securities lending market

Coverage

According to DataExplorers, their dataset now covers approximately 90% of the securities lending market. This encompasses around 3.5 million transactions per day, involving around 220,000 individual equity and debt instruments. In terms of history, the daily database starts in July 2006.[4] Figure 4 shows the number of Russell 3000 stocks which have stock loan data over time. Coverage overall is good, but like many of the new databases we have explored in the past year (e.g. options data, industry-specific data, news sentiment data, tick-by-tick data) the biggest drawback is the short history. We elaborate on this point later in this report.

Figure 4: Number of stocks in Russell 3000 index with stock loan data



Source: DataExplorers, Russell, Deutsche Bank

Academic evidence

Short interest has been a hot topic in academia, with most authors finding some predictive power

Before tackling the data itself, it is worth highlighting the current state of the academic literature. In recent years there have been a plethora of studies testing the predictive power of stock loan data, and in particular short interest. On balance, most of the research does seem to find some predictive power, although the usual caveats about transaction costs and implementation issues apply.

Recent papers that have found that high short interest predicts future underpeformance include Deither, Lee, and Werner [2009], Boehmer, Jones, and Zhang [2008], and Engelberg, Reed, and Ringgenberg [2010]. In addition, Boehmer, Huszar, and Jordan [2009] find that most of the performance differential between highly and lightly shorted stocks actually comes from the long side, i.e. buying stocks that have low short interest.

Figure 5 summarizes the latest academic papers on short interest. Of particular interest to us is Engelberg, Reed, and Ringgenberg [2010], which finds that the advantage of short sellers comes from a better ability to interpret public news. This suggests a natural extension of our news sentiment research, i.e. can we enhance a short interest signal by focusing on stocks

[4] Note DataExplorers also has monthly and weekly data going back to 2002, but these data did not use the same quality control procedure that is applied to the daily data. In this study, we focus on the daily data from 2006 onwards.

with recent news?[5] Also of interest is Boehmer, Jones, and Zhang [2008]. This paper finds that institutional, non-program short sales are most informative. Of course, we can't identify these trades in real-time, but perhaps we can use the Probability of Informed Trading idea that we explored recently to at least guess at which short trades are being driven by "informed" traders.[6] We explore both these ideas in this study.

Figure 5: Recent academic papers on short interest

Authors	Title	Result
Deither, Lee, Werner [2009]	"Short-sale strategies and return predictability"	Short sellers correctly predict future negative abnormal returns. A trading strategy based on daily short-selling activity generates significant positive returns during the sample period
Boehmer, Jones, and Zhang [2008]	"Which shorts are informed?"	Heavily shorted stocks underperform lightly shorted stocks in the next 20 days. The most informative short sales are institutional non-program short sales.
Boehmer, Huszar, and Jordan [2009]	"The good news in short interest"	Stocks with low short interest experience statistically and economically significant positive abnormal returns in the future. In contrast, the negative future performance of stocks with low short interest is transient and not economically significant.
Engelberg, Reed, and Ringgenberg [2010]	"How are shorts infomed? Short sellers, news, and information processing"	The finding that short sellers predict negative future returns is twice as strong in the presence of news stories. The advantage of short sellers derives from their ability to process publicly available information.
Berkman and McKenzie [2010]	"Earnings announcements: Good news for institutional investors and short sellers"	Pre-announcement changes in institutional holdings and short interest have significant explanatory power in predicting abnormal earnings announcement returns

Source: Deutsche Bank

The securities lending market

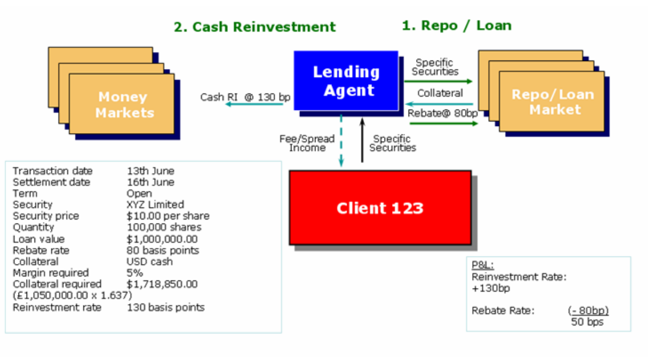
Currently there is around $12 trillion in lendable inventory, of which around $2 trillion is currently on loan

The securities lending market is an over-the-counter (OTC) market in which participants lend and borrow securities. Needless to say, for quant investors in particular this market is of critical importance. According to DataExplorers, total available inventory in the securities lending market is roughly US$ 12 trillion, of which around US$ 2 trillion is currently on loan. During the financial crisis these numbers declined sharply, and the current level is still lower than the pre-financial crisis level of around $15 trillion. In terms of asset classes, approximately 54% of this market is comprised of equities and the rest is debt instruments.[7]

Because the securities lending market is OTC, the mechanics of borrowing a security can differ depending on the transaction. However, broadly speaking there are two types of transactions: those collateralized with cash, and those collateralized with securities. To borrow a security, the borrower will typically need to post some form of collateral to protect the lender in case the borrower defaults. Figure 6 and Figure 7 summarize each scenario.

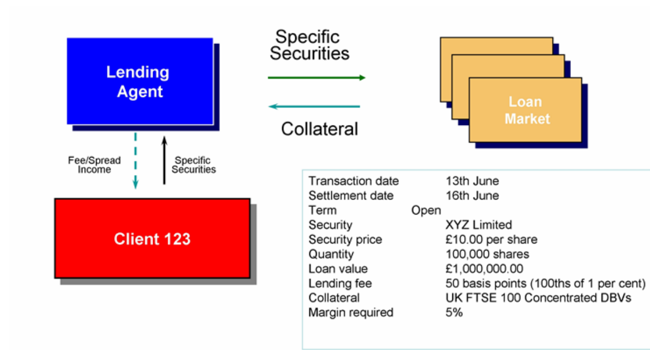
[5] Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010, "Signal Processing: Beyond the headlines", *Deutsche Bank Quantitative Strategy*, 7 September 2010
[6] Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010, "Signal Processing: Frequency arbitrage", *Deutsche Bank Quantitative Strategy*, 10 November 2010
[7] See Faulkner [2010] and DataExplorers [2011] for more details.

Figure 6: Stock loan process: Cash collateral



Source: DataExplorers

Figure 7: Stock loan process: Non-cash collateral



Source: DataExplorers

In the U.S. most borrowing is secured against cash collateral

In the U.S. market, most transactions are carried out using cash collateral, with almost 97% of transactions executed this way (Faulkner [2010]). This is in contrast to other regions like the U.K. (15%) and Canada (13%). In a cash-collateralized transaction, the borrower of the security posts cash collateral and receives a rebate from the lender for some of the returns generated while the collateral is held by the lender. The profit to the lender is the difference between the rate the lender reinvests the cash collateral at and the rate the lender rebates back to the borrower.

For a detailed explanation of the mechanics and evolution of the securities lending market, Faulkner [2010] is a good starting point.

Univariate backtests

Where to start?

We start our analysis by backtesting a wide range of potential factors on a univariate basis

The typical reaction when quants are faced with a new database is almost universal: backtest, backtest, backtest, and then backtest some more. This report is no exception. We first backtest a wide range of potential factors on a univariate basis, and then narrow down our research to focus on specific factors that we believe make intuitive sense as alpha signals. From there we branch out to explore the real-world implications of using factors based on stock loan data, and detail some of the advantages and pitfalls of incorporating this information into an investment process.

Figure 8 gives some examples of the types of factors that are either available in the DataExplorers database, or can be easily calculated by combining data items from the database with other market and fundamental data points. A complete list of all factors and definitions can be found in the appendix. As mentioned previously, the factors can be loosely classified into four buckets: demand, supply, utilization, and cost of borrow.

Figure 8: Examples of potential securities lending factors

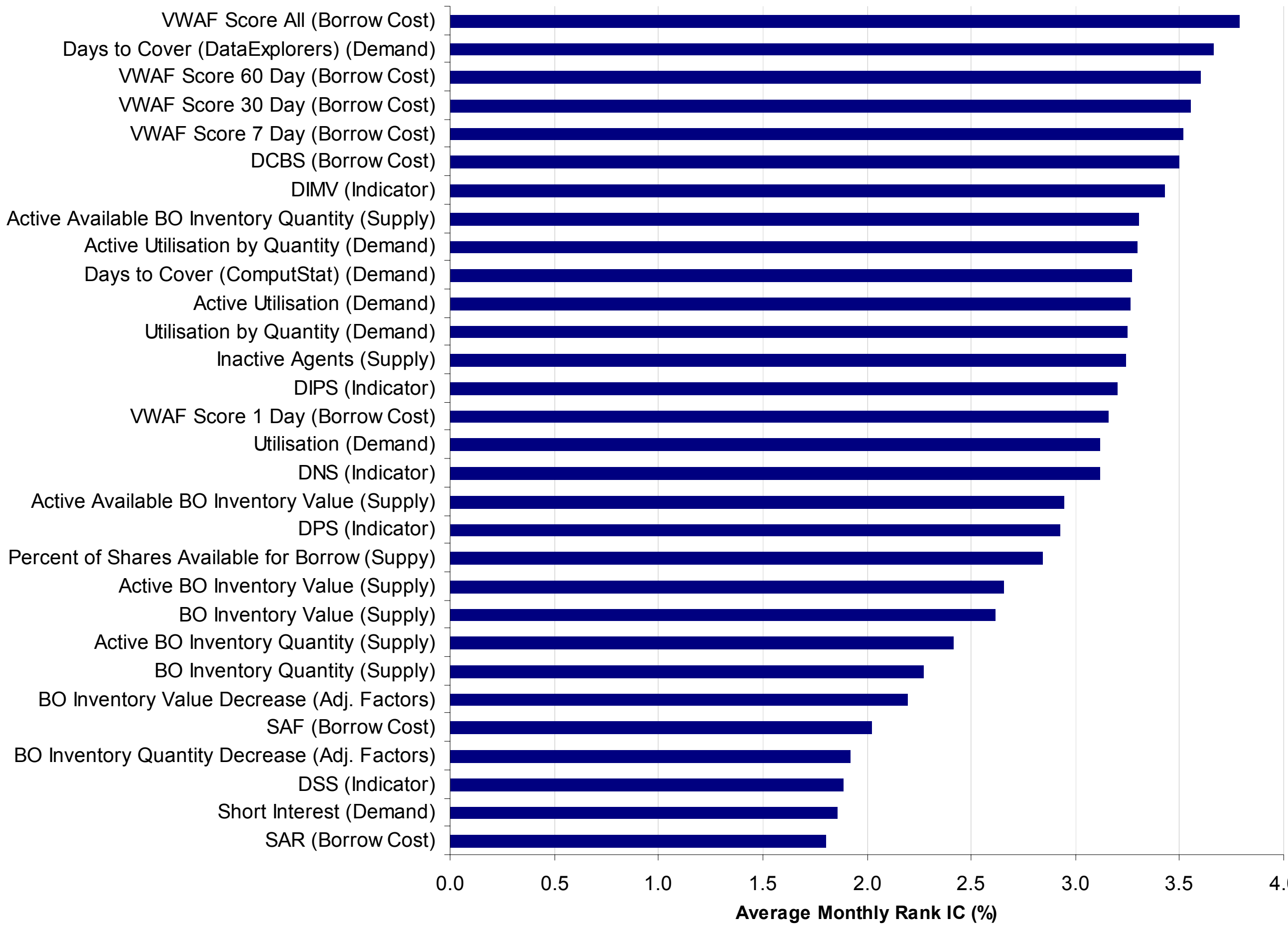
Type	Examples	Definition	Rationale
Demand	Total Demand Quantity	Total quantity of borrowed/loaned securities net of double counting	Designed to capture the amount of stock that is currently being borrowed. Most of the traditional short interest metrics that quants use fall into this category.
	Short Interest	Total Demand Quantity / Shares on Issue	
	Days to Cover	Total Demand Quantity / Average Daily Volume	
Supply	Active Agents	Number of custodians and lending agents with open transactions	Measures the amount of stock that is available for lending. Can be a proxy for institutional ownership, because it is almost exclusively institutional investors who make their holdings available for lending.
	Active Available BO Inventory Quantity	Quantity of shares realistically available for borrowing by removing Beneficial Owner On Loan Quantity from Active Beneficial Owner Inventory Value	
	Percent of Shares Available for Borrow	Active Available Beneficial Owner Inventory Quantity / Shares on Issue	
Utilization	Active Utilization	Demand value as a % of the realistically available supply (Beneficial Owner On Loan Value / Active Beneficial Owner Inventory Value)	A fusion of the supply and demand categories. Measures the percent of available inventory that is currently being lent out. Potentially a useful measure for identifying short squeeze candidates, where the available supply of lendable stock is becoming exhausted.
	Change in Utilization, 1M	One month change in Active Utilization	
Borrow Cost	VWAF Score 30 Day	Value Weighted Average Fee for all new trades on the most recent 30 calendar days expressed in undisclosed fee buckets 0-5, where 0 is the cheapest to borrow and 5 the most expensive	Measures the cost of borrowing a particular stock. This can either be from the perspective of a custodian bank or broker who pays the beneficial owner (e.g. DCBS) or a hedge fund who pays a prime broker (e.g. SAF/SAR)
	DCBS	Data Explorers Daily Cost of Borrow Score; a number from 1 to 10 indicating the rebate/fee charged by the agent lender based on the 7 day weighted average cost, where 1 is cheapest and 10 is most expensive	
	SAF	Simple average fee of stock borrow transactions from hedge funds in this security	
	SAR	Simple average rebate of stock borrow transactions from hedge funds in this security	

Note: A complete list of factors and definitions can be found in the Appendix.
Source: DataExplorers, Deutsche Bank

To get things started, Figure 9 shows a simple ranking of stock loan factors, based on monthly backtesting from 2006 to now over the Russell 3000 universe. The performance metric used is the average monthly rank information coefficient (IC) over the backtest period.

We will define these factors in more detail shortly, but for now we are just interested in getting a rough feel for performance.[8]

Figure 9: Best 30 factors sorted by average monthly rank information coefficient (IC), 2006-now



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Over the time period for which we have lending data, many of these factors perform well…

On face value performance is promising…

Even at this very preliminary level, two things stands out. First, over the same 2006-present period, the average rank IC performance of the "traditional" quant factors that we regularly track was about 2%, and the cutoff for the top performance quintile was around 3%.[9] So at a superficial level, the performance of factors based on stock loan data looks very favorable, especially when we consider that the last five years (which is the period we have stock loan data) has been arguably the most difficult since the inception of quant investing.

…but a critical question is how much it will cost to trade the short side of these signals

…but there is an important caveat

Second, it is noticeable that the top of the ranking in Figure 9 is dominated by what we call "cost of borrow" factors. Essentially these factors capture the cost of borrowing, or shorting, each stock. In other words, they go long stocks that are cheap to borrow, and short stocks that are expensive to borrow. This result suggests an important caveat to the first point. Yes, performance at a first pass looks promising, but there is a real risk that none of this paper

[8] Exact factor definitions are included in the Appendix.

[9] Average and quintile cutoff metrics were calculated over a set of approximately 80 representative quant factors that we track regularly in our research. For a complete list of these factors, see page 3 of Luo et al., 2011, "QCD Model: QCD model update", *Deutsche Bank Quantitative Strategy*, 6 January 2011

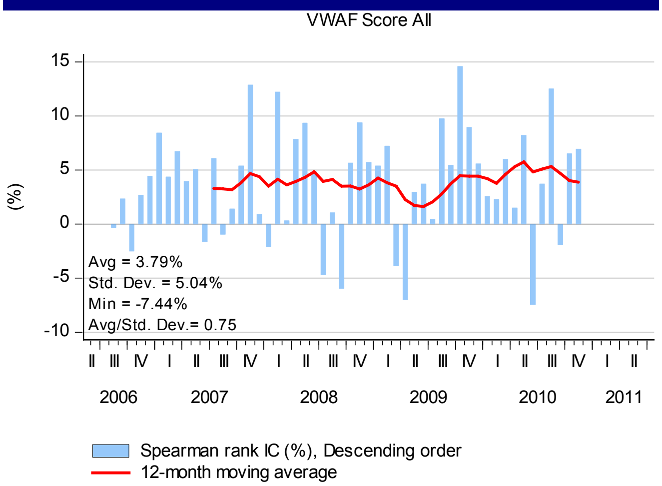
performance can be harvested in a real-world portfolio. It may be that these factors work only because they tend to take short positions in stocks that are already costly to borrow. If this is the case, then the factor performance we are seeing here may simply reflect a limit to arbitrage, and not a realizable alpha. Even for factors not based on cost of borrow – for example Days to Cover – it may be that there is a high cross-sectional correlation with cost of borrow, which would take us to the same problematic place.

In the rest of this report, we focus on disentangling these two competing hypotheses. Specifically, we seek ways to use stock loan factors in the investment process, without simply loading the short side of the portfolio with hard to borrow names that underperform on paper but can't be shorted in real life.

Time-series performance

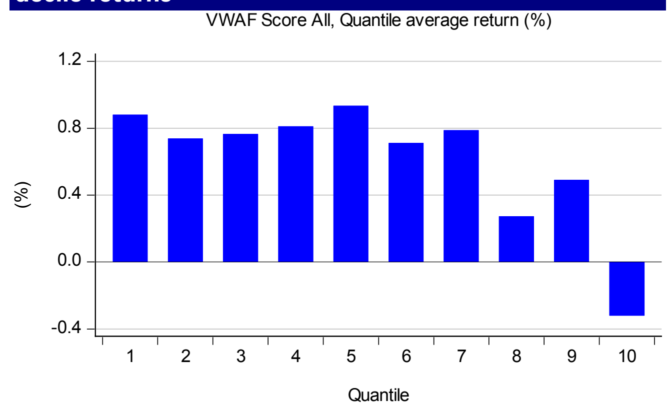
Before diving into the rest of the research, it's worth looking at some of the factors on a time-series basis. Figure 10 shows the monthly rank IC performance for the VWAF Score All factor, and Figure 11 shows the average monthly returns to decile portfolios.

Figure 10: VWAF Score All backtest, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 11: VWAF Score All backtest, average monthly decile returns



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Cost of borrow factors perform very well, but a long-short investor cannot necessarily take advantage of this alpha due to borrowing costs

The VWAF Score All factor is a factor that captures a value weighted average of the stock borrow fee for each stock. Looking at the time-series performance for the factor (Figure 10), the hit rate in terms of positive months is extremely high. In fact, it's so high that it seems too good to be true – and probably is. If we look at the average returns to decile portfolios (Figure 11) we can see that a lot of the performance is coming from Decile 10, which contains the stocks that are most expensive to borrow. Clearly these stocks underperform, but the question is whether they underperform by enough to make up for their high borrow costs.[10] We will come back to these points in the next section.

Outside of the cost of borrow factors, one of the best performing factors is also one of the simplest: Days to Cover. This factor is, as far as we can tell, commonly used by quantitative managers and is computed by dividing the current number of shares sold short for a stock by the average daily volume for that stock. However, it is usually computed using stock exchange provided short interest data, which is typically snapped only twice a month and as

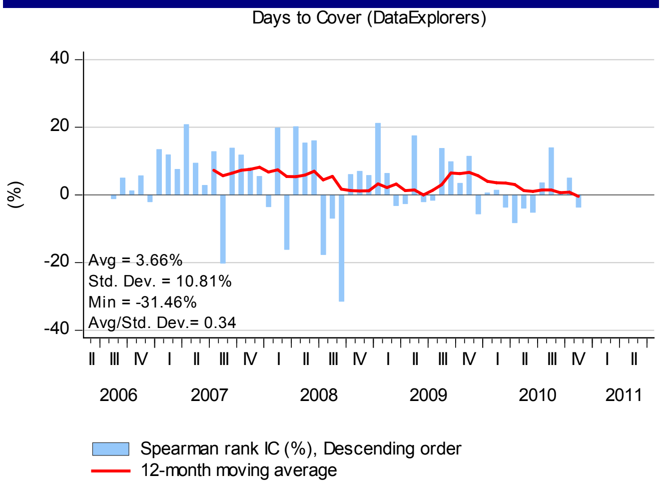
[10] Also keep in mind the cost of borrow is only an issue for long-short investors. Long-only investors can of course underweight high borrow cost stocks for free, and thus potentially capture more of the alpha from this factor than a long-short investor. We return to this point in our portfolio simulations later in this report.

a result can be quite stale depending on when in the month factor scores are computed.[11] In contrast, we use DataExplorer data to calculate this factor. As discussed in the previous section, this data is almost real-time and hence allows for timelier factor calculations.

Days to Cover is a promising factor that measures how many days of trading it would take to cover all short positions

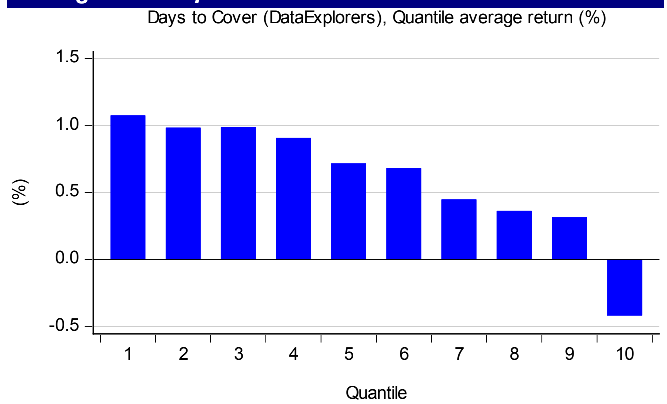
As shown in Figure 12, the Days to Cover factor has worked reasonable well over the short history for which we have data, albeit with some signs of decaying performance in more recent years. Like the cost of borrow factors, a lot of performance is being driven by Decile 10, which in this case contains stocks where it would take a long time to cover all the shorts based on recent trading volume. Again, the pertinent question is whether we can actually harvest any of the alpha from the short side. As mentioned, we will address this issue in the next section.

Figure 12: Days to Cover (DataExplorer) backtest, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 13: Days to Cover (DataExplorer) backtest, average monthly decile returns



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

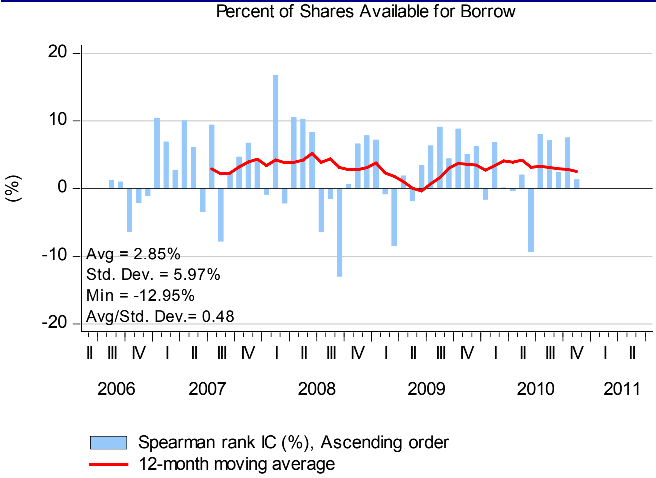
The next factor we consider is one based on the supply side, i.e. what percent of total shares on issue are currently available for lending. This factor is computed by taking the total inventory available from beneficial owners and subtracting the current shares out on loan, and then normalizing by the total shares on issue. The idea is to capture how much inventory is still available for borrowing in each stock. Again, the time-series performance appears quite good (Figure 14), particularly when compared to most the traditional factors over this same period.

The Percent of Shares Available to Borrow is a factor that captures the available supply of lendable stock as a percentage of total shares outstanding

On average, stocks with a high percent of shares available for borrow outperform. This is somewhat intuitive – if a stock has as large percentage of its shares available for borrowing it potentially means two things. First, the stock is likely to have greater institutional ownership since it is almost exclusively institutional investors who lend stock. Second, most of the stock available for borrow has not yet been lent out. Once again, however, there are potential implementation issues (for long-short managers at least) in the sense that most the performance comes from the extreme short decile (Figure 15).

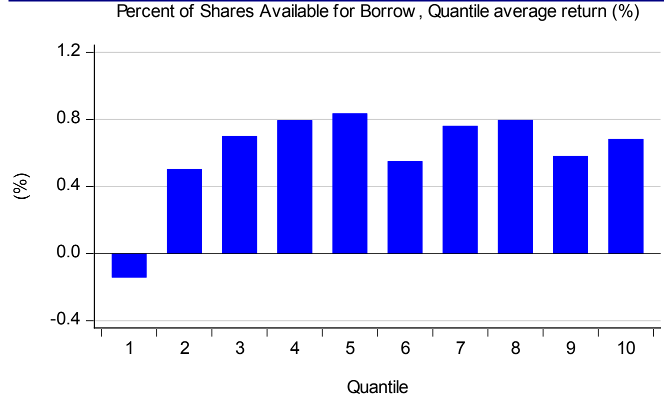
[11] For example, we previously computed Days to Cover using Compustat data. Compustat obtains their short interest data from each stock exchange, and typically this data is snapped around mid-month. So when computing the factor at the end of each month, the data is already stale by around 15 days.

Figure 14: Percent of Shares Available to Borrow backtest, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 15: Percent of Shares Available to Borrow backtest, average monthly decile returns

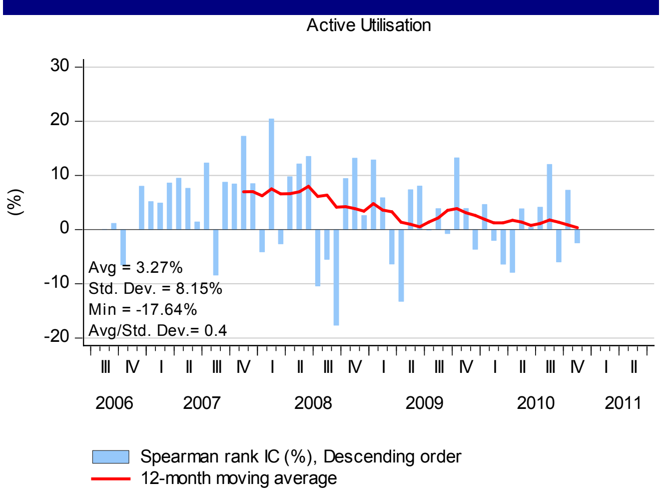


Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Active Utilization measures the percentage of lendable stock that is currently being borrowed

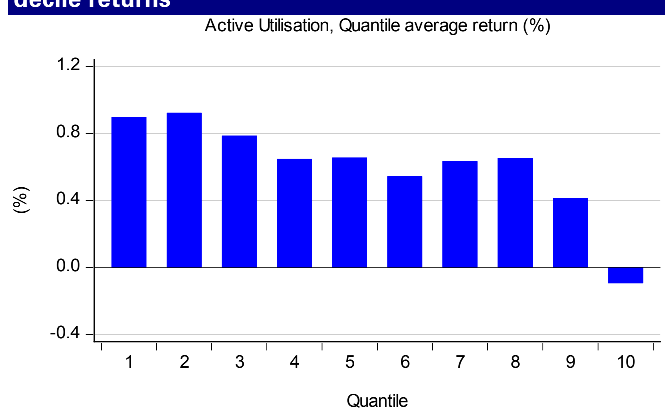
Another interesting factor that we can get from the DataExplorer database is a metric called Active Utilization.[12] This factor is similar to the previous factor, except it measures the number of shares that are currently lent out as a percentage of the total shares available for borrow (the previous factor measured the number of shares available for lending as a percentage of the total shares on issue). The idea is to get a sense for whether most of the available borrow for a particular stock has been used up. Figure 16 and Figure 17 show that on average high utilization is bad, at least on average over the next month.

Figure 16: Active Utilization backtest, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 17: Active Utilization backtest, average monthly decile returns



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

This is an interesting finding because one hypothesis would be that high utilization could be a warning sign for a short squeeze because it implies that those who might want to borrow the stock (and hence have a negative view) can no longer do so. This may be true, but on average at least these results suggest that stocks with high utilization actually underperform

[12] The "Active" in the name refers to the fact that DataExplorers has pre-screened the data to eliminate double counting between the data supplied by stock lenders and stock borrowers. In the DataExplorers database, both a stock lender and a stock borrower may submit data for each side of a single loan transaction. To avoid counting these transactions twice, DataExplorers uses a set of algorithms to match and eliminate double counting.

in the following month rather than rally. We will examine the case of short squeezes in more detail in the next section.

Where to next?

The univarite results show some promise, but we still need to consider the critical question of costs

The univariate results are promising enough to suggest further research is warranted. On paper, a number of the factors highlighted above show quite a bit of promise in terms of ranking stocks cross-sectionally, but as mentioned a crucial question is how much of this alpha can be harvested in a real portfolio. Factors based on stock loan data are also somewhat unique in that there is a real asymmetry in terms of implementation; because of cost of borrow considerations the alpha available to a long-short investor may be very different from what can be captured by a long-only manager.

Building a composite signal

Which factors to pick?

Rather than pick a few individual factors, we construct a composite signal in the hope of getting some diversification benefit

In this section, we focus on building a composite factor that captures the best information available in the securities lending data. The idea is to pick a subset of all the factors that show good performance individually, but also have a relatively low correlation with each other. We've used this idea before when exploring new datasets, for example our DB Composite Options Factor, which we construct from a unique options database.[13]

But which factors should we pick? Figure 18 shows the top 30 potential factors ranked across three standard performance metrics: rank IC, sector-neutral rank IC, and Decile 10 – Decile 1 return spread. The final sort is done based on the average rank across all three.

Figure 18: Best 30 factors sorted by average rank across three performance metrics, 2006-now

		RANK			
Factor	**Type**	**Average Monthly Rank IC**	**Average Monthly Sector-Neutral Rank IC**	**Average Q10-Q1 Decile Spread**	**Average Rank**
VWAF Score All	Borrow Cost	1	1	7	3
VWAF Score 30 Day	Borrow Cost	4	3	6	4
VWAF Score 60 Day	Borrow Cost	3	2	8	4
Days to Cover (DataExplorers)	Demand	2	12	2	5
VWAF Score 7 Day	Borrow Cost	5	4	10	6
DIMV	Indicator	7	6	9	7
DCBS	Borrow Cost	6	5	12	8
Active Utilization by Quantity	Demand	9	9	13	10
Days to Cover (ComputStat)	Demand	10	19	4	11
Active Utilizations	Demand	11	11	14	12
Utilization by Quantity	Demand	12	10	16	13
DIPS	Indicator	14	7	17	13
Utilization	Demand	16	15	18	16
DNS	Indicator	17	13	19	16
Active Available BO Inventory Quantity	Supply	8	17	26	17
VWAF Score 1 Day	Borrow Cost	15	8	28	17
DPS	Indicator	19	16	20	18
Inactive Agents	Supply	13	14	29	19
Percent of Shares Available for Borrow	Suppy	20	25	23	23
BO Inventory Value New	Adjustment Factors	42	35	1	26
Open Loan Transactions	Demand	31	31	21	28
Short Interest	Demand	29	24	31	28
BO Inventory Value	Supply	22	22	42	29
DSS	Indicator	28	23	36	29
Active BO Inventory Value	Supply	21	21	50	31
BO Inventory Quantity New	Adjustment Factors	36	27	30	31
Active Agents	Supply	39	34	22	32
SAF	Borrow Cost	26	26	46	33

Note: Factors highlighted in grey are those selected for use in the composite signal.
Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

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[13] Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010, "Signal Processing: The options issue", *Deutsche Bank Quantitative Strategy*, 12 May 2010

Due to the short history, we are forced to manually select factors for the composite, something we usually try to avoid

In the end, we pick the three factors highlighted in grey for use in a simple, equally weighted composite signal. We call this signal the DBSL factor (which stands for Deutsche Bank Security Lending factor). The rationale for picking these three factors is not because they are the best performing. Rather, we pick them for a few reasons:

- **Diversification:** We intentionally pick a mixture of supply and demand based factors, even though the supply factor (Percent of Shares Available to Borrow) in particular ranks at the lower end of all three performance metrics. Hopefully drawing from both sides of the supply-demand equation will give us better diversification across our factors.
- **No cost of borrow factors*:*** We avoid picking any cost of borrow factors, despite the fact this is the group of factors that perform the best in our univariate backtesting. Our argument is these factors give good paper performance, but will be hard to implement for the cost of shorting reasons that we have discussed.
- **Intuition:** We intentionally steer towards simple, intuitive factors. All three of the factors we pick are easy to understand and transparent. For example, Percent of Shares Available to Borrow is actually not the best supply-side factor; that honor goes to Active Available BO Inventory Quantity (which is essentially the same thing – the number of shares available for loaning out – except it is not scaled by shares on issue). We argue that it makes more sense to scale available inventory by shares on issue, rather than use the raw number, which suffers from a size bias.

A word of caution

The short history and the large number of potential factors mean there is a significant risk of data mining

Notwithstanding the above arguments, a word of caution is prudent. Usually in our research, we try to avoid manually selecting factors after the fact. For example, in our QCD stock-selection model, we intentionally design a set of algorithms to automatically select factors at each point in time without human intervention.[14] Our argument is that even with the best of intentions, it is almost impossible to avoid picking the factors that worked well in the past, which of course introduces a look-ahead bias. However, with the stock loan data it is difficult to build any automatic factor selection algorithm because the data history is so short.

This is a problem we've come up against before; in fact, for all the new databases we've explored over the last year (e.g. options data, industry-specific data, news sentiment data, tick-by-tick data) the biggest limitation has been the lack of history. Needless to say, the shorter the history, the bigger chance that any promising results are purely statistical noise or are specific to a certain set of macroeconomic conditions. Where the tipping point lies is probably more of a philosophical question that each quant needs to justify in their own mind. In our case we do feel we have enough history to draw some interesting conclusions, but a healthy degree of skepticism is always warranted when dealing with a short history.

Factor correlations

Getting back to the results, Figure 20 shows the time-series correlation for the three factors we include in the composite.

Figure 19: Time-series correlation of selected stock loan factors

	Days to Cover (DataExplorers)	Active Utilization	Percent of Shares Available for Borrow
Days to Cover (DataExplorers)	1		
Active Utilization	0.79	1	
Percent of Shares Available for Borrow	0.74	0.70	1

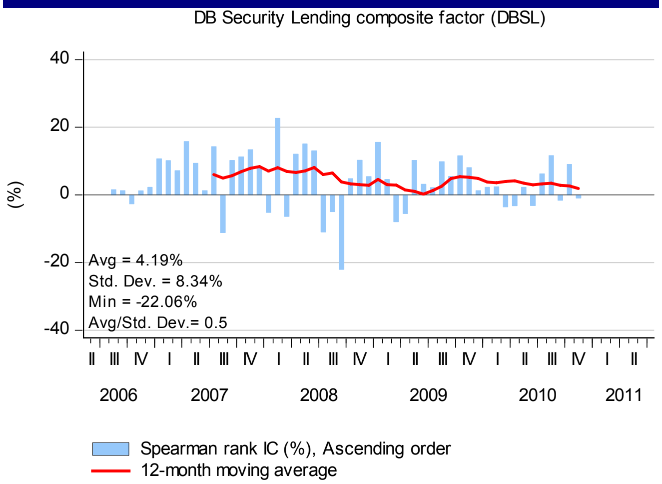
Source: DataExplorers, Deutsche Bank

[14] Luo, Y., R. Cahan, J. Jussa, and M. Alvarez, 2010, "QCD Model: DB quant handbook", *Deutsche Bank Quantitative Strategy*, 22 July 2010

Correlations between our selected factors are high, but we still get some moderate diversification benefit

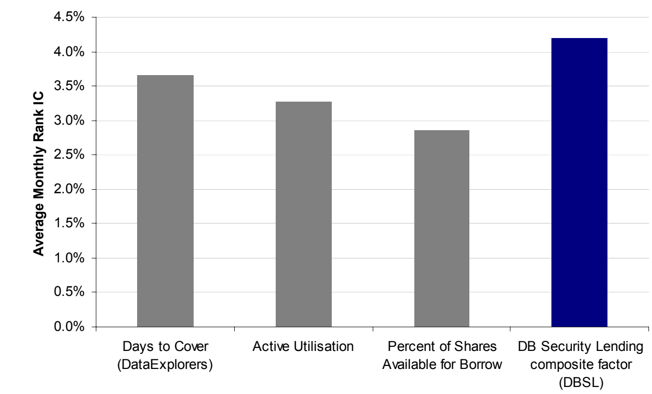
The correlations are fairly high – above 70% - so each of the three factors is to some extent capturing some of the same information. However, even with these fairly high correlations, we still get some diversification benefit from combining the three factors. Figure 20 shows the rank IC performance of the DBSL factor, and Figure 21 compares the average rank IC for each constituent factor to the composite factor. The composite factor on average outperforms each of the three constituent factors, indicating we are indeed picking up some diversification benefit. The average rank IC of 4.19% is actually very good for this time period, and would rank the factor in the top 10% of all the quant factors we track.

Figure 20: DBSL backtest, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

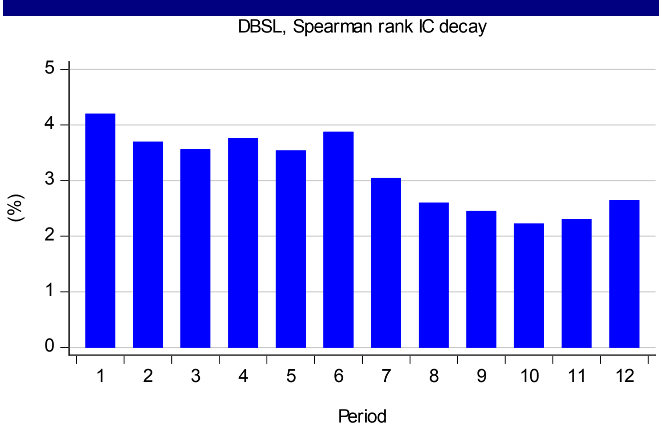
Figure 21: DBSL performance compared to constituent factors, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

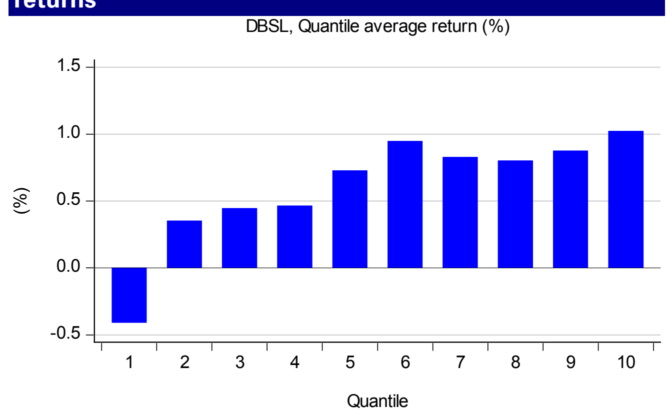
Another attractive feature of the DBSL factor is that it has a relatively slow information decay rate (Figure 22). Even after 12 months there is still some predictive power in the signal, which means from an implementation perspective turnover will not be a major issue.

Figure 22: DBSL backtest, rank IC decay profile



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 23: DBSL backtest, average monthly decile returns



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Finally, Figure 23 shows the average decile portfolio returns. Much like the underlying factors, a lot of the performance for the DBSL composite factor is coming from the extreme short side of the signal. This brings us to the most important question of all: can we actually harvest any of this apparent alpha?

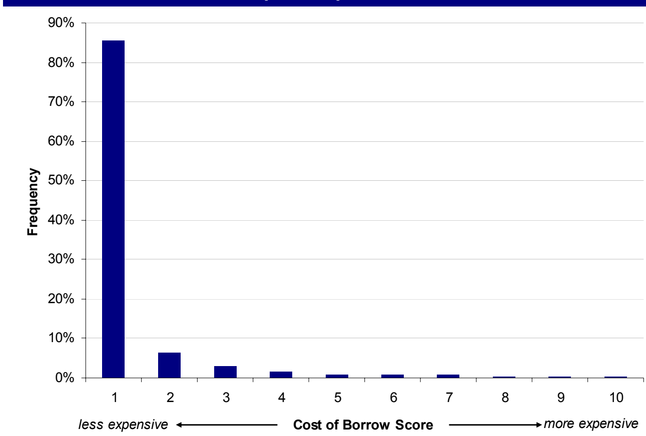
Adjusting for shorting costs

For long-short quant investors, the most important question is whether we can actually capture the alpha on the short side once borrow costs are considered

Fortunately, the DataExplorers database provides some of the raw data needed to answer this question. One of the metrics provided in the database is a data item called DCBS, which is a score from 1 to 10 representing the cost of borrowing a particular stock (1 being the cheapest to borrow, and 10 being the most expensive). Figure 24 shows the percentage of the universe (in our case the Russell 3000) that falls into each bucket. The majority of stocks fall into the first bucket (i.e. cheap to borrow) and the percentage in each subsequent bucket declines exponentially from there.

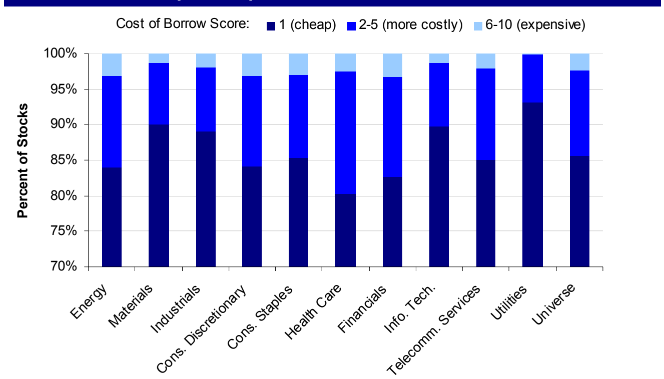
If we look at the distribution by sector (Figure 25) it appears that the hard to borrow stocks are relatively evenly spread across the 10 GICS sectors. As we might expect, the more "speculative" and volatile sectors like Energy and Health Care tend to have a slightly higher proportion of hard to borrow stocks.

Figure 24: Frequency distribution for whole universe, by Cost of Borrow Score (DCBS)



Source: DataExplorers, Deutsche Bank

Figure 25: Frequency distribution by sector, by Cost of Borrow Score (DCBS)

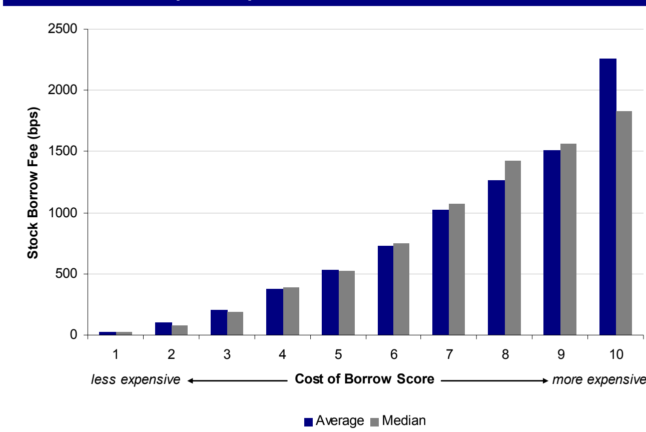


Note: Y-axis scale starts at 70% to better illustrate the more expensive tail of the distribution

Source: DataExplorers, Deutsche Bank

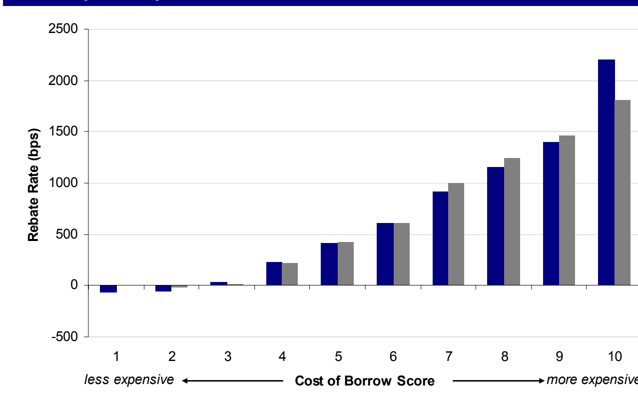
So how much does a "hard to borrow" stock actually cost? Putting a number on this is quite hard, because the cost of borrowing a stock will depend on a large number of factors. But very roughly speaking Figure 26 and Figure 27 give some indication of likely costs.

Figure 26: Average Stock Borrow Fee (SAF) by Cost of Borrow Score (DCBS)



Source: DataExplorers, Deutsche Bank

Figure 27: Average Rebate (SAR) by Cost of Borrow Score (DCBS)



Source: DataExplorers, Deutsche Bank

The cost data from DataExplorers suggests that borrowing costs can be prohibitive if not managed proactively

The two charts above show the average stock borrow fee (SAF) and rebate rate (SAR) that hedge fund borrowers face when shorting stocks in each fee bucket. Essentially SAF and SAR measure the same thing, i.e. the cost of borrow for a buy-side firm to borrow the stock from a prime broker. The reason there are two separate metrics is more of a technicality: for trades booked with cash collateral, the fee is quoted as a rebate rate (SAR) because the lender will rebate the return on the collateral back to the borrower. For trades with non-cash collateral the cost of borrowing is quoted as a straight fee (SAF).[15]

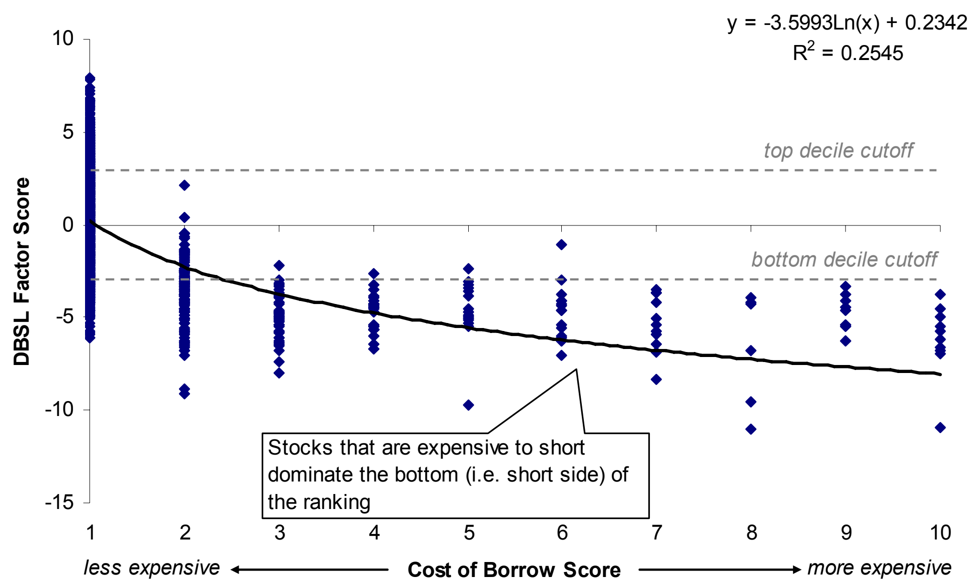
While the numbers in Figure 26 and Figure 27 are annualized, it is still clear that shorting the most expensive stocks can be prohibitively expensive.

Our composite DBSL factor has a significant exposure to hard to borrow names on the short side

How exposed is the composite signal to hard to borrow stocks?

With this in mind, it is clear we need to be very careful about how much exposure our composite factor has to expensive to borrow stocks. Figure 28 shows one way we can think about this. For one point in time, we plot the factor score of each stock as a function of the cost of borrow bucket (measured by the DCBS score). What we can clearly see is that most of the stocks that fall below the bottom decile cutoff (and hence would end up in the short portfolio) are coming from the more expensive cost buckets.

Figure 28: DBSL before adjusting for shorting costs, as at 30-Nov-2010



Source: DataExplorers, Deutsche Bank

This can be a major problem, depending on how we choose to implement the signal. If we are a long-short investor, then using the signal in its raw form is going to be difficult, if not impossible, because almost all of the short side of the portfolio is going to be expensive to borrow. However, if we are a long-only investor, we may well be able to stop here, because we only need to go underweight the hard to borrow stocks.[16] For the rest of our analysis, we

[15] Note that there is also a distinction between DCBS, the cost of borrow score, and SAF/SAR. DCBS measures the cost that brokers pay to custodian banks or other brokers, whereas SAF/SAR represents the cost that hedge funds pay to prime brokers. However, DCBS has a cross-sectional correlation of 0.86 with both SAF and SAR, so essentially all metrics are measuring the same thing, i.e. the cost of borrow.

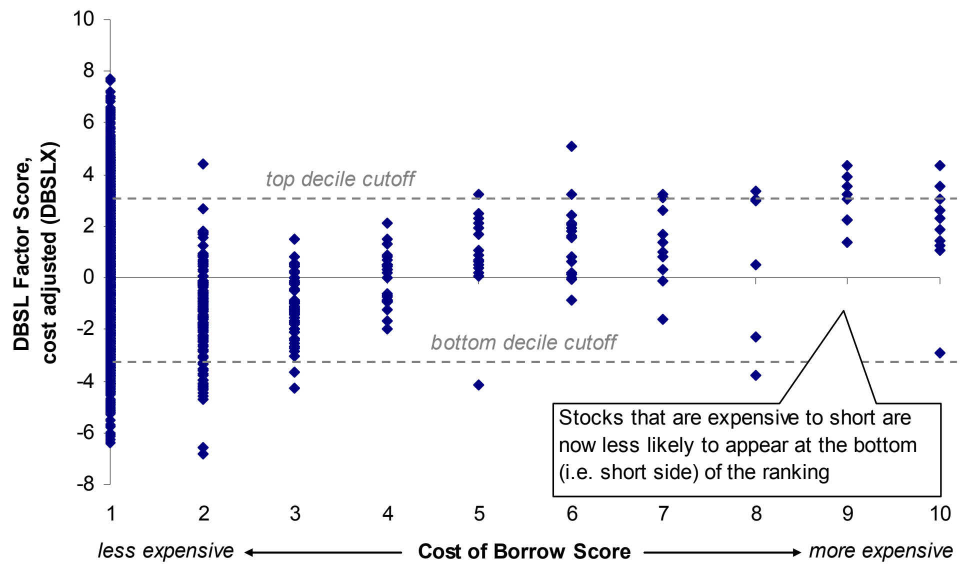
[16] However, even if we are a long-only investor we may still have issues capturing the full alpha of the signal if it turns out that hard to borrow names are skewed towards small cap stocks. Because a long-only investor can only go underweight up to the benchmark weight, he/she may still be restricted in how much of the negative side of the factor can be captured. We present a more realistic long-only simulation in the next section.

assume we will implement the signal in a long-short portfolio (we return to the long-only case in our portfolio simulations at the end of this section).

We use a simple cross-sectional regression to control for cost of borrow at each point in time

Looking back at Figure 28, one simple adjustment we could make to the factor is to regress the factor scores cross-sectionally onto the DCBS scores. In other words, we only want to short stocks that rate poorly on the factor, *after* controlling for the cost of borrowing that stock.[17] If we do a regression of the composite factor score onto the log of the cost of borrow score, then we can use the residual as our "cost-adjusted" factor score (Figure 29). We call this new cost-adjusted version of the factor DBSLX (the "X" representing the cross-sectional regression).

Figure 29: DBSL after adjusting for shorting costs, as at 30-Nov-2010



Source: DataExplorers, Deutsche Bank

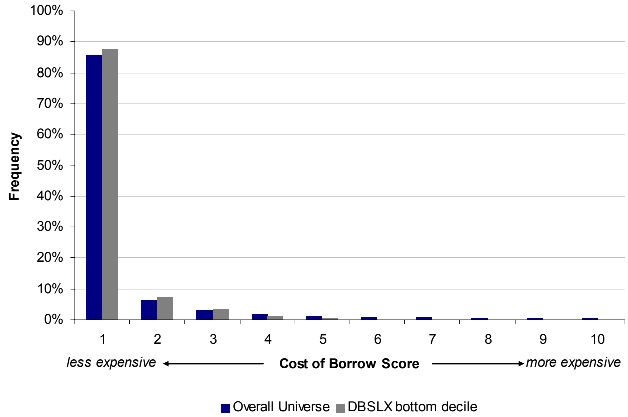
Once we make this adjustment, we can see from the chart that most of the stocks falling below the bottom decile cutoff now come from the cheapest to borrow bucket. In fact, many of the most expensive to borrow names have now been pushed up to have positive factor scores, meaning we probably won't need to short them at all.

The adjustment effectively penalizes stocks that are hard to borrow

Another way to visualize the effect of this adjustment is to look at Figure 30. In these charts we show the percentage of stocks within Decile 10 of the cost-adjusted factor (DBSLX) that come from each cost bucket. We compare this to the proportions for the overall universe. In Figure 31 we show the same thing, except we zoom in on the most expensive cost buckets. What we can see is that the short basket (i.e. Decile 10) of the cost-adjusted factor in fact has less exposure to hard to borrow names than the overall universe. This is a good outcome, because we are almost certain to need to short most of the stocks in Decile 10 if we want to implement the factor in a real-life long-short portfolio.

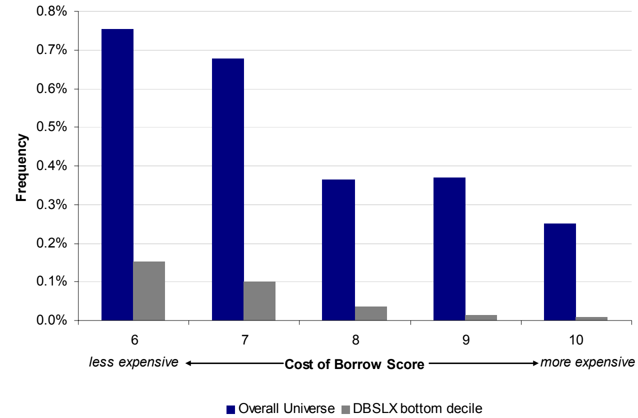
[17] As an aside, one could also argue that this adjustment should be made at the portfolio construction step instead of at the factor level, i.e. we should include the cost of borrow in our optimizer (either in the objective function or as a constraint) and then let the optimizer determine what the appropriate trade off is between the expected return for the stock and the cost of trading the stock. In this exercise we prefer to adjust the factor because we think it is a little more transparent, but we don't have a strong argument against the optimizer approach either. In fact, both will probably get you to roughly the same place.

Figure 30: Percentage of stocks that fall into each cost bucket



Source: DataExplorers, Deutsche Bank

Figure 31: Percentage of stocks that fall into five most expensive cost buckets

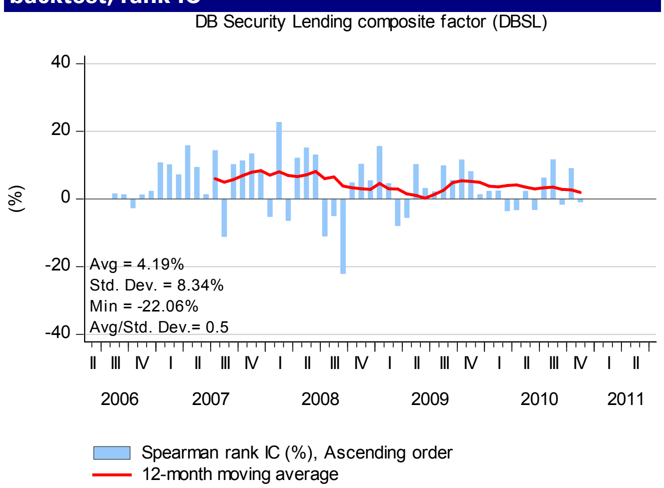


Source: DataExplorers, Deutsche Bank

Of course, the cost adjustment hurts the raw factor performance, but keep in mind we are now roughly talking about after cost performance

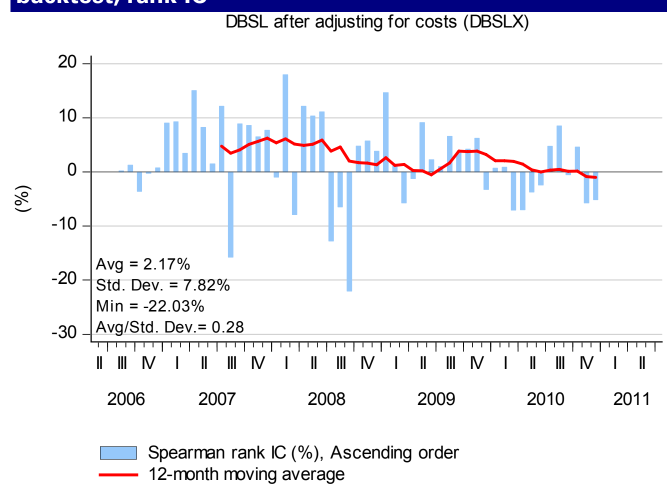
But what about performance? Does the alpha in the signal survive this cost adjustment procedure? Figure 32 and Figure 33 show the rank IC performance of composite factor, before and after our cost adjustment. As expected, the performance falls quite a bit. However, keep in mind the IC we are looking at now is – in a loose sense – an after-cost performance metric, and as a result we need to benchmark the performance against the after-cost performance of other factors. We will discuss this more in our portfolio simulation analysis.

Figure 32: DBSL (i.e. before cost adjustment regression) backtest, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 33: DBSLX (i.e. after cost adjustment regression) backtest, rank IC



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Enhancing the signal with overlays

Academic literature suggests there are ways we can interact securities lending data with other factors

After cost adjusting our factor, we think we have a signal that shows some promising predictive power, so we could stop here and move on to testing the signal under more real-world conditions. However, we were intrigued by some of the recent academic literature that suggests that short interest signals work particularly well in certain subsets of stocks or under certain conditions. Can we use these ideas to further enhance our signal?

Engelberg, Reed, and Ringgenberg [2010] find that stocks with high short interest and news stories tend to underperform even more

Interaction with news sentiment

Last year in *Signal Processing* we showed how Natural Language Processing (NLP) algorithms can we used to automatically quantify the "sentiment" of a news article based on the language and grammatical structure of the story. We went on to show that a sentiment factor constructed in this way can add incremental alpha to a quant model because it tends to be relatively uncorrelated with existing quant styles. Given our findings, we were particularly intrigued by a recent academic paper by Engelberg, Reed, and Ringgenberg [2010]. In the paper, the authors show that the ability of short sellers to predict negative returns actually derives from their ability to interpret publicly available news. Specifically they find that the ability of short selling to predict negative returns is twice as strong for stocks with news stories compared to those without news stories.

To investigate this interesting interaction effect, we carry out a simple double sort analysis. We first partition our universe at each point in time into quintiles based on news sentiment, and then backtest our DBSLX factor within each sub-universe.[18] Figure 34 shows the results. Each cell in the matrix represents the average monthly return in the subsequent month for stocks in that particular subset.

Figure 34: Double sort on news sentiment and then DBSLX factor, average monthly return for equally weighted portfolio

		Poor DBSLX Score Q1	Q2	Q3	Q4	Good DBSLX Score Q5
Negative Sentiment	**Q1**	0.05	0.87	0.58	0.59	1.08
	Q2	0.42	1.23	1.16	0.37	0.94
	Q3	0.48	1.19	0.57	0.61	0.62
	Q4	0.37	0.34	0.78	0.77	0.82
Positive Sentiment	**Q5**	0.35	0.66	0.66	0.72	0.62

Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

The interesting feature of Figure 34 is that the worse performing subset is stocks that rank poorly on the DBSLX and also have negative news sentiment. This is consistent with the academic finding, because it suggests that heavy shorting is a particularly good signal when it is accompanied by negative news.

Boehmer, Jones, and Zhang [2008] show that institutional non-program short sales are most predictive of future underperformance

Interaction with informed trading

Another interesting academic finding, put forth in Boehmer, Jones, and Zhang [2008], is that the most informative short trades are those executed by institutions via non-program trades. This makes intuitive sense, because non-program trades are more likely to capture short sales that represent a fundamentally negative view on a stock, as opposed to a quant rebalance (more likely to be done via a program trade), which might just be shorting stocks for risk control or arbitrage reasons. However, Boehmer et al. are quick to point out that their finding does not translate into a trading strategy, because their data are unobservable in real-time (they use proprietary order-flow data which is not publicly available).

Nonetheless, we can think of two potential ways to proxy for stocks with more institutional trading: options volume and the probability of informed trading. Both these metrics could offer a way to identify stocks that have greater institutional trading, and hence a subset of stocks where the DBSLX factor might have greater efficacy.

[18] In this research we define sentiment as $\sum_{n=1}^{N} \text{Relevance}_n \times (\text{Probability Story is Positive}_n - \text{Probability Story is Negative}_n)$ where *N* is the number of news stories in the past month for that stock. We use the Reuters News Analytics database as our source for the news data. This is a simplified definition compared to what we used in our news sentiment research. For exact definitions of each input, see: Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010, "Signal Processing: Beyond the headlines", *Deutsche Bank Quantitative Strategy*, 7 September 2010.

We proxy this idea with the option to stock volume ratio and the probability of informed trading

Figure 36 shows another double sort, this time sorting first on a factor called the O/S ratio. The O/S ratio is the dollar value of options traded relative to the dollar value of stock traded. A high O/S ratio indicated greater options activity, and potentially greater institutional trading.[19] The results here are not as clear cut as they are for news sentiment, but roughly speaking stocks in the extremes of the DBSLX factor (both positive and negative) appear to underperform more when they also have high options volume relative to stock volume.

Figure 35: Double sort O/S ratio and then DBSLX factor, average monthly return for equally weighted portfolio

		Poor DBSLX Score Q1	Q2	Q3	Q4	Good DBSLX Score Q5
Low O/S	Q1	0.40	0.85	0.97	1.21	1.12
	Q2	0.51	1.17	0.63	0.57	0.73
	Q3	0.73	0.81	0.64	0.27	0.63
	Q4	0.33	0.54	0.29	0.09	0.82
High O/S	Q5	0.16	0.19	0.53	0.08	0.11

Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

The final double sort is done using our RPIN factor.[20] Again, the results are somewhat mixed, but it does appear that the worse underperformers are those stocks in Q1 of DBSLX that also have a high risk of informed trading.

Figure 36: Double sort on RPIN and then DBSLX factor, average monthly return for equally weighted portfolio

		Poor DBSLX Score Q1	Q2	Q3	Q4	Good DBSLX Score Q5
Low Informed Trading	Q1	0.73	1.12	0.79	0.64	1.17
	Q2	1.19	1.25	1.31	1.39	1.10
	Q3	0.39	0.74	0.41	0.63	0.70
	Q4	0.12	0.75	0.56	0.86	0.66
High Informed Trading	Q5	0.24	0.65	0.51	0.50	0.35

Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

Adding it all up

In isolation the improvement from each overlay is limited, but collectively the cumulative performance increase is substantial

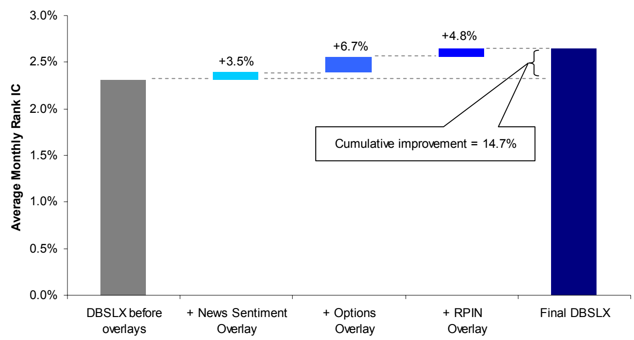
What happens if we overlay these three factors on top of our DBSLX factor? We do this in a very simple way. At each point in time, we first normalize (i.e. z-score) the DBSLX factor score. Then, for stocks that fall in Q1 of the news sentiment factor we simply add the normalized news sentiment factor score to the DBSLX z-score (this penalizes these stocks because stocks in Q1 based on news sentiment will have a very negative sentiment score).

We can also do the same with RPIN and O/S, except in these cases we penalize stocks with high informed trading and high O/S. To measure the impact of these overlays on the DBSLX signal, we add each in turn and re-backtest the signal. Figure 35 shows the cumulative improvement in average monthly rank IC as we add each overlay. Figure 36 shows the same except for risk-adjusted performance. In isolation each overlay makes a fairly modest improvement in performance, but taken together the enhancement to the signal is reasonably significant – adding about 15% in IC terms and 28% in risk-adjusted terms.

[19] For more information on the O/S ratio factor, see: Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010, "Signal Processing: The options issue", *Deutsche Bank Quantitative Strategy*, 12 May 2010

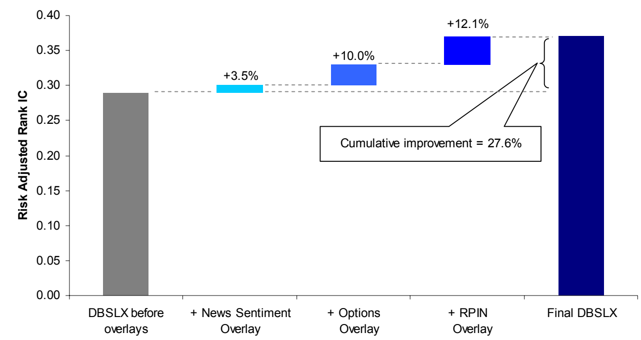
[20] RPIN is a factor we developed to measure the probability of informed trading, after controlling for size, volatility, and liquidity. For more details, see: Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010, "Signal Processing: Frequency arbitrage", *Deutsche Bank Quantitative Strategy*, 10 November 2010

Figure 37: Cumulative improvement in signal efficacy from overlays



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

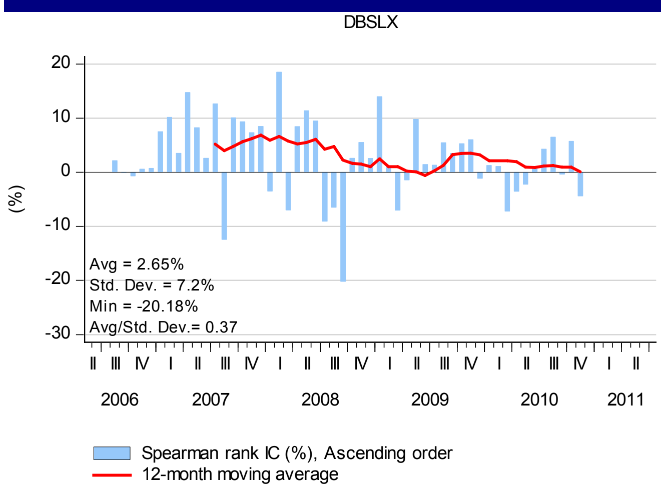
Figure 38: Cumulative improvement in risk-adjusted signal efficacy from overlays



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

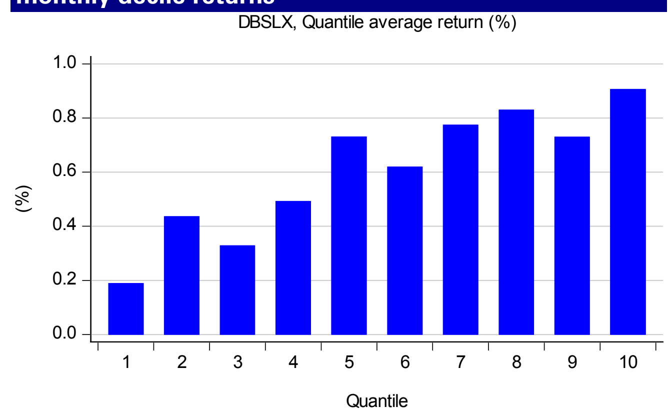
Re-backtesting the signal with the cost adjustment plus the three overlays, we get Figure 39. Overall the performance of the signal is quite promising, although like almost all quant factors it has shown a steady performance decay in more recent years. The decile return profile is also reasonably monotonic, which is of course another desirable feature for a candidate factor (Figure 40).

Figure 39: DBSLX after adding overlays, rank IC



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

Figure 40: DBSLX after adding overlays, average monthly decile returns

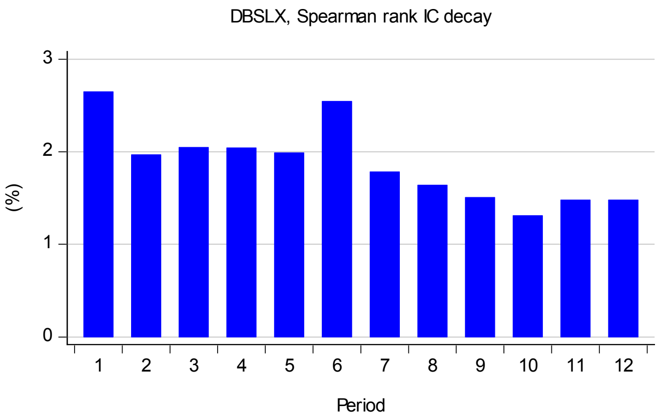


Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

The DBSLX factor shows a relatively slow information decay profile, which means turnover will be moderate

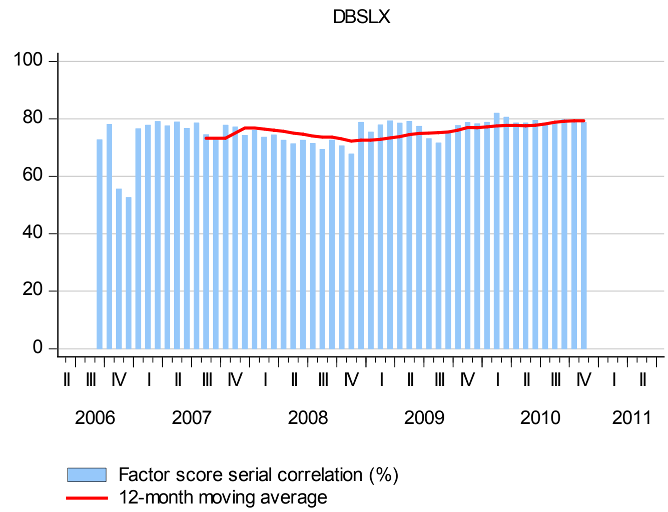
The factor also has a slow information decay profile (Figure 41), which is interesting given that two of the three overlays (options and news sentiment) are quite high turnover. As an aside we think this is a great illustration of how we can extract some of the alpha in high turnover factors, without incurring all of the turnover, by using them as overlays or conditioning tools. Figure 42 shows the autocorrelation of the signal from month to month, which confirms that the factor is actually reasonably stable through time.

Figure 41: DBSLX backtest, rank IC decay profile



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

Figure 42: DBSLX backtest, signal autocorrelation



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

Avoiding squeezes

One of the biggest concerns for short sellers is the risk of a short squeeze, where a stock pops sharply and borrowers have to scrabble to cover their short positions, further fueling the rally

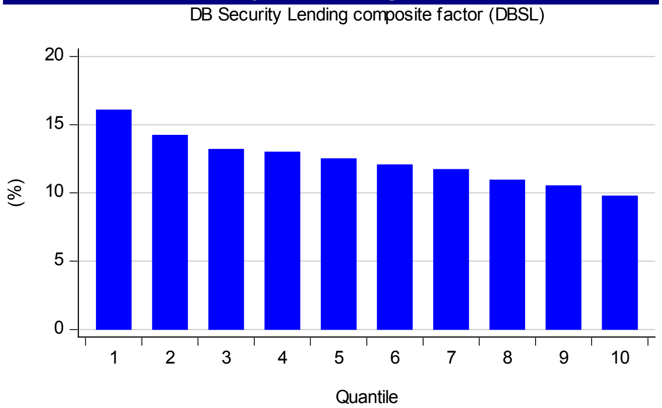
Despite having adjusted the factor for costs and enhanced it with overlays, there is still a lingering concern: the dreaded short squeeze. Of all the reasons for avoiding shorting, one of the most frequently cited is the unlimited downside (for a short investor) when a stock rallies sharply with no (theoretical anyway) upper bound. Such a rally can often be triggered by a so-called short squeeze, i.e. a heavily shorted stock that begins to rally and then is further driven up as short sellers are forced to buy stock to cover their increasingly untenable short positions. Our backtesting shows that *on average* stocks in the bottom deciles tend to underperform in the next month. This average is a little dangerous because it may disguise significant cross-sectional dispersion in returns within the short portfolio, i.e. there may be many stocks that have a moderate negative return in the next month but a few "squeeze" stocks that have very large positive returns that are being masked by the average.

One way to test this is to look at the cross-sectional return dispersion in each decile of the DBSLX factor. Figure 43 and Figure 44 show the return dispersion of one month forward returns by decile for the pre- and post-cost adjustment composite factor, respectively. Before we do the cost adjustment, the worse decile (1) has the highest return dispersion, while the best decile (10) has the lowest. This is evidence that our hypothesis about squeeze stocks hiding in the bottom decile may have some merit. However, when we consider the cost adjusted version of the factor (DBSLX), we find that the excess dispersion in the bottom deciles has disappeared. This is promising, because it suggests our cost adjustment has had the unexpected side benefit of helping to remove extreme returns from the bottom decile.

Our cost adjustment helps steer the DBSLX factor away from potential squeeze candidates, since these stocks are usually costly to borrow

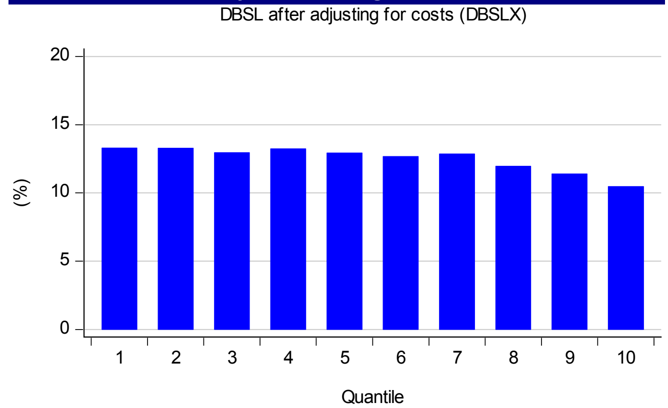
This is somewhat intuitive. The most likely candidate for a short squeeze will typically be a stock that has become expensive to borrow. A high cost of borrow can reflect the fact that demand for shares to borrow is significantly outstripping supply. This in turn can trigger a short squeeze because new shorts cannot get the borrow they need to continue to push the stock down. By tilting our factor away from expensive to borrow names, we also implicitly reduce the risk of exposing the short side of the portfolio to extreme positive performers.

Figure 43: Cross-sectional forward return volatility by decile, before cost adjustment regression



Source: DataExplorers, Deutsche Bank

Figure 44: Cross-sectional forward return volatility by decile, after cost adjustment regression



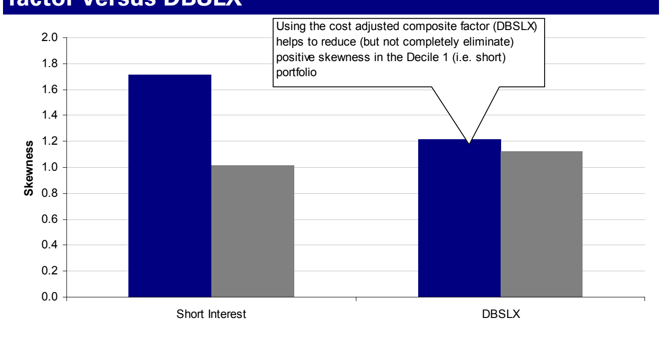
Source: DataExplorers, Deutsche Bank

The cost adjustment also helps remove excess skewness and kurtosis in forward returns for stocks that rank poorly on the DBSLX factor

More evidence for this conclusion comes from looking at the cross-sectional skewness and kurtosis of one month forward returns within each decile. In Figure 45 we look at the difference in skewness for Decile 1 compared to Deciles 2-10, for the basic short interest factor and the DBSLX factor. We find there is a significant difference in skewness between the bottom decile and the rest of the universe, when ranking stocks by short interest. In other words, the short portfolio constructed based on simple short interest would be exposed to high positive skewness (i.e. a few large, positive outliers). This is a bad thing for a short investor. In contrast, the DBSLX factor avoids this imbalance.

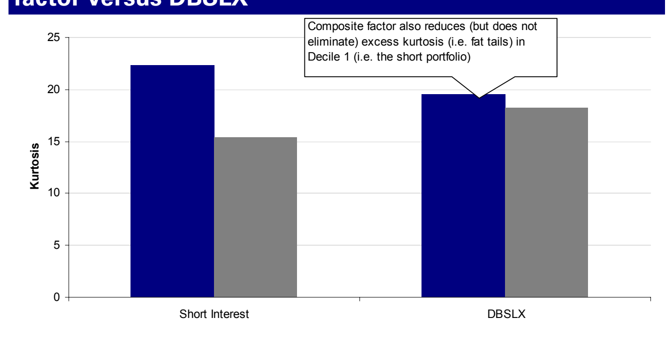
We get a very similar picture if we consider kurtosis (Figure 46). Again, the short decile for the short interest factor suffers from significant kurtosis (i.e. fat tails) compared to the rest of the deciles, while the DBSLX factor does not.

Figure 45: Skewness by decile for simple short interest factor versus DBSLX



Source: DataExplorers, Deutsche Bank

Figure 46: Kurtosis by decile for simple short interest factor versus DBSLX

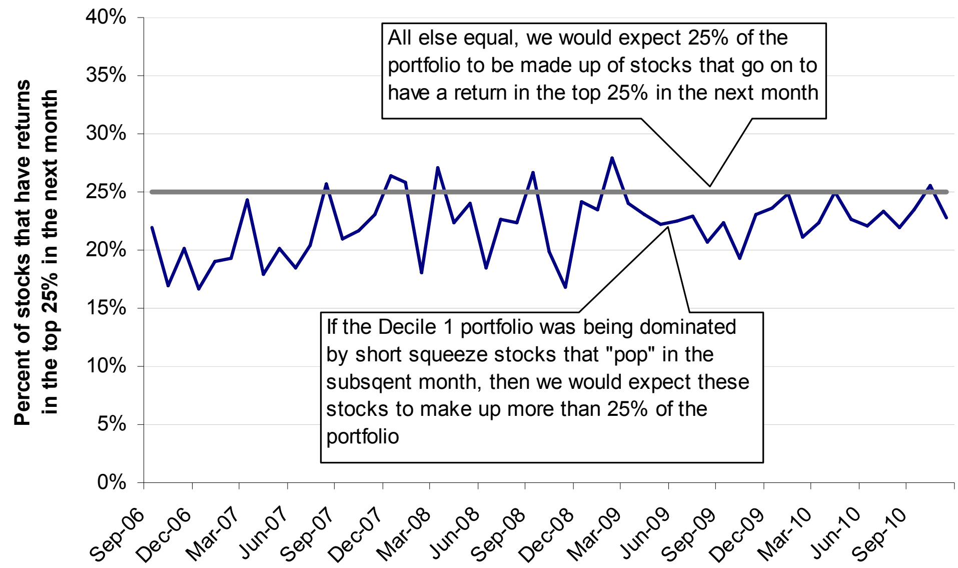


Source: DataExplorers, Deutsche Bank

The DBSLX short portfolio on average contains a lower percentage of stocks that jump in the subsequent month, compared to the overall universe

These results give us some comfort that the short side of our DBSLX factor is not unduly exposed to potential short squeeze candidates. Nonetheless, we also examine the percentage of stocks in Decile 1 of the DBSLX factor that go on to have a large positive performance (defined as being in the top 25% of returns) in the following month. Clearly for the universe as a whole this number will be around 25% by definition. But what about the bottom decile? Figure 47 shows a time-series of the result. On average the bottom decile based on our factor has less that 25% of the stocks that pop in the next month. This further reinforces our view that we don’t have a significant exposure to short squeeze stocks.

Figure 47: Percentage of stocks in decile 1 that jump in the subsequent month



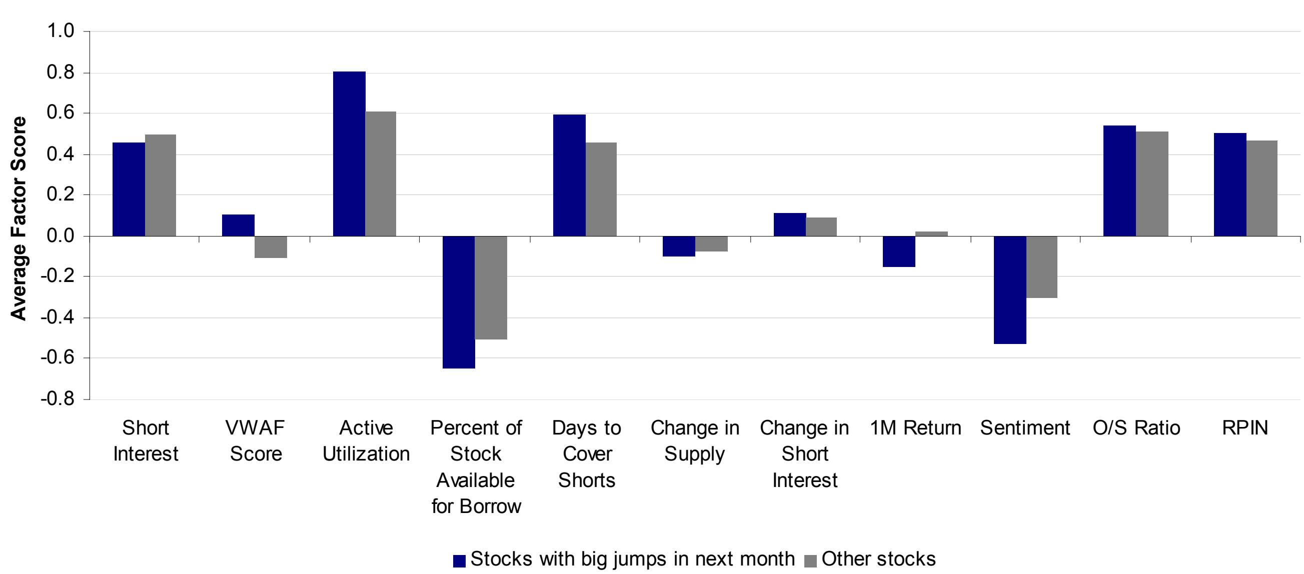
Source: DataExplorers, Deutsche Bank

Short squeeze forensics

Identifying short squeeze candidates from their factor scores is difficult

While our DBSLX factor appears to be doing a relatively good job at avoiding potential squeezes, perhaps we can do better than the statistics in Figure 47. Maybe, if we can identify the "fingerprint" of a short squeeze candidate, we could filter such stocks out of the short portfolio and make our factor even better. Figure 48 makes an attempt to do this. In the chart we measure the average factor score for stocks that end up having big positive returns in the next month, and those that don't. We restrict the universe to stocks in the bottom decile based on the composite factor. This is in line with our desire to eliminate jump stocks from the short portfolio.

Figure 48: Average factor scores for stocks with and without a large jump in the subsequent month, conditional on stock being in bottom decile based on DBSLX

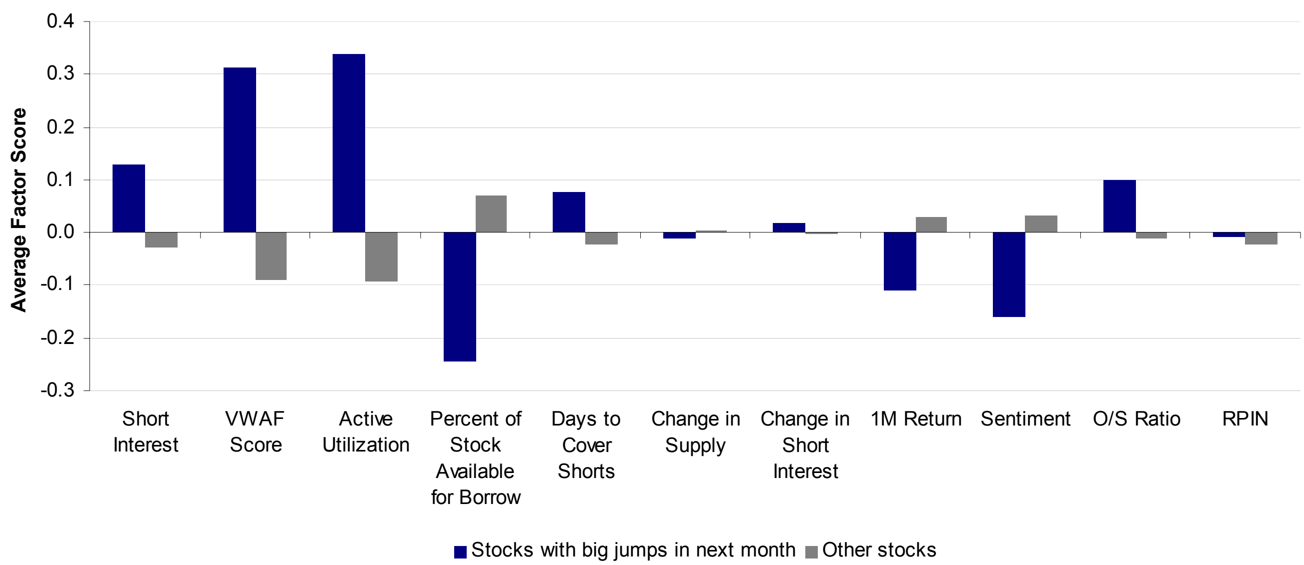


Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

Interestingly, there are a few results that make a lot of sense. For example, stocks that go on to have large positive returns next month tend to have higher utilization, which means demand is starting to outstrip supply. They also have a higher VWAF (cost of borrow) score, which further implies demand is stretching available supply. As well, stocks that jump tend to be reversal candidates, i.e. they have more negative one-month returns and more negative news sentiment, suggesting they may have bottomed out and are on their way back up.

However, looking at the big picture the two groups of stocks are more similar than they are different (partly by construction since we are restricting ourselves to the worse decile of our DBSLX factor). We tried quite a few ways to extract a useful "anti-squeeze" overlay based on this fingerprint idea, but couldn't come up with anything that improved performance much.

Figure 49: Average factor scores for stocks with and without a large jump in the subsequent month, whole universe



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, eDerivatives, Deutsche Bank

As one final piece of analysis, we also include Figure 49, which shows the same chart except for the whole universe. This picture is quite interesting, because here we see a significant difference between stocks that have future large positive returns and those that do not. Taking this further is beyond the scope of this particular paper, but it does suggest interesting future research that might use stock loan data to identify what we might call "reverse torpedoes", i.e. stocks that go on to have a large one-month jump.

Correlation with existing factors

The correlation of DBSLX with other common quant factors is one of the most important questions

The next step with any new factor is to assess its correlation with existing factors. Even the most exciting new factor will add little real value if it is just a linear combination of existing factors. In most of our research we tend to use time-series performance correlation as our main measure of correlation; after all at the end of the day that is what really matters. But given the short history we are dealing with for this factor, we also look at the average cross-sectional correlation over time.

Figure 50 shows the 10 most positive correlations, both cross-sectional and time-series. Because of the short history, the rankings based on the two correlation metrics are more different than we would ordinarily expect.

Figure 50: Largest positive correlations between DBSLX and other factors

CROSS-SECTIONAL CORRELATION		TIME-SERIES CORRELATION	
Factor	**Average Monthly Cross-Sectional Correlation (%)**	**Factor**	**Monthly Rank IC Correlation (%)**
Log float-adj capitalization	30.3	IBES 5Y EPS growth	73.3
QCD Model	21.9	QCD Model	72.2
Normalized abnormal volume	20.5	Hist 5Y operating EPS growth	68.8
# of month in the database	19.4	Log float-adj capitalization	66.2
Earnings yield, forecast FY1 mean	19.2	Recommendation, mean	64.8
Sector-relative Operating earnings yield, trailing 12M, Basic	18.6	Hist 5Y operating EPS stability, coef of determination	62.6
21D volatility of volume/price	18.2	Campbell, Hilscher, and Szilagyi model	59.7
Earnings yield, forecast FY2 mean	17.8	IBES SUE, amortized	57.8
Return on invested capital (ROIC)	17.1	IBES FY1 EPS up/down ratio, 3M	57.7
EBITDA/EV	17.0	IBES FY1 mean EPS growth	56.0

Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

The most problematic correlation is with size; this probably needs to be controlled at the portfolio construction step

The most positive cross-sectional correlation is with size – stocks that rate well on the DBSLX factor tend to be larger cap stocks, while stocks that rate poorly tend to be small caps. This correlation also carries over into the performance correlation table, where size is the fourth most correlated factor. This is problematic, because it does suggest that the factor is something of a size proxy, and is something that may need to be controlled at the portfolio construction step. The factor is also somewhat correlated with our QCD stock selection model. This is not necessarily a bad thing, after all our QCD model has performed relatively well over time. However, it does mean the hurdle rate for adding incremental alpha is going to be higher, since some of the alpha in the DBSLX factor is already being captured by other factors in that model.

Figure 51: Largest negative correlations between DBSLX and other factors

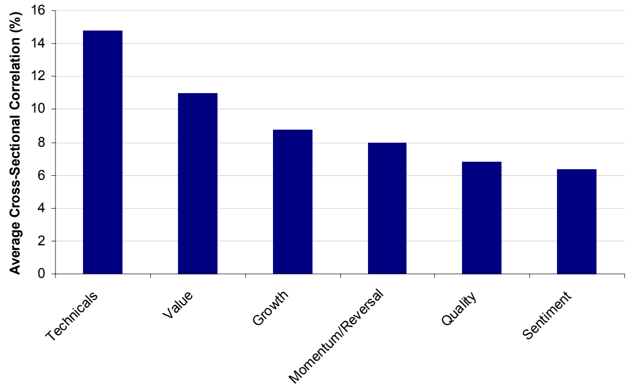
CROSS-SECTIONAL CORRELATION		TIME-SERIES CORRELATION	
Factor	**Average Monthly Cross-Sectional Correlation (%)**	**Factor**	**Monthly Rank IC Correlation (%)**
Operating profit margin	-6.8	Price-to-book	-0.5
CAPM beta, 5Y monthly	-3.1	Payout on trailing operating EPS	-0.5
Payout on trailing operating EPS	-2.2	Dividend yield, trailing 12M	-0.5
Long-term debt/equity	-1.4	IBES FY1 mean CFPS growth	-0.5
Total return, 1D	-1.4	Expected dividend yield	-0.5
Altman's z-score	-1.0	Float turnover, 12M	-0.5
Total return, 21D (1M)	-1.0	Free cash flow yield	-0.4
YoY change in debt outstanding	-0.5	IBES LTG EPS mean	-0.4
Accruals (Sloan 1996 def)	0.0	Price-to-book adj for ROE, sector adj	-0.3
Price-to-book	0.2	Price-to-sales, trailing 12M	-0.2

Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 51 shows the same results on the negative side. On both correlation metrics the negative correlations are fairly small in magnitude, which reflects the fact that it is very difficult to find a factor that has a negative correlation with other common factors. Most of the time, the best we can do is to try to find the smallest positive correlation that we can.

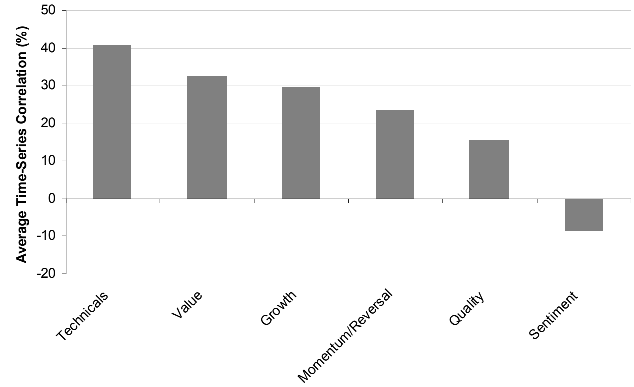
To summarize the correlation results, we show the average cross-sectional (Figure 52) and time-series (Figure 53) correlations for each of the six style buckets we use in our research.

Figure 52: Average cross-sectional correlation between DBSLX and six style buckets



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 53: Average time-series rank IC correlation between DBSLX and six style buckets



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

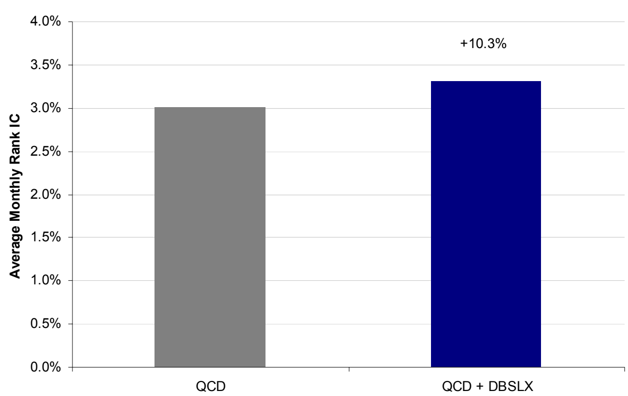
Real-world simulation

We use our QCD model as a benchmark, and investigate whether we can add value by incorporating the DBSLX factor into the model

The final step in our analysis is to test the DBSLX signal in a more realistic portfolio simulation. To do so we start with our QCD model as our base case alpha signal, and then add in the DBSLX factor as an additional alpha factor at a 20% weight. This is a fairly high hurdle rate, because our QCD model has delivered relatively good performance over our 2006-present backtest period.

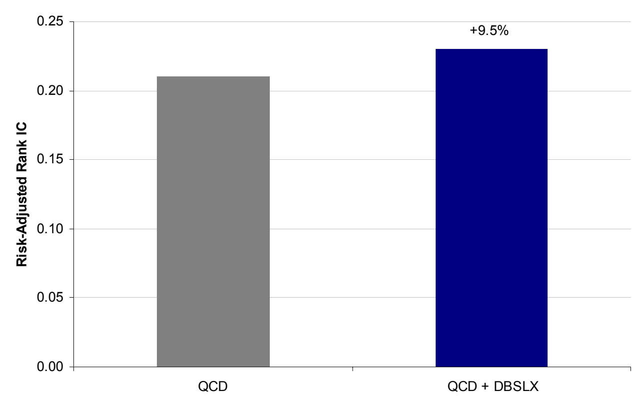
Before getting to the simulations, Figure 54 and Figure 55 show that in terms of simple rank IC, and also risk-adjusted rank IC, adding the DBSLX to the QCD model does boost performance by around 10%.

Figure 54: QCD improvement when adding DBSLX, average monthly rank IC



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 55: QCD improvement when adding DBSLX, risk-adjusted monthly rank IC



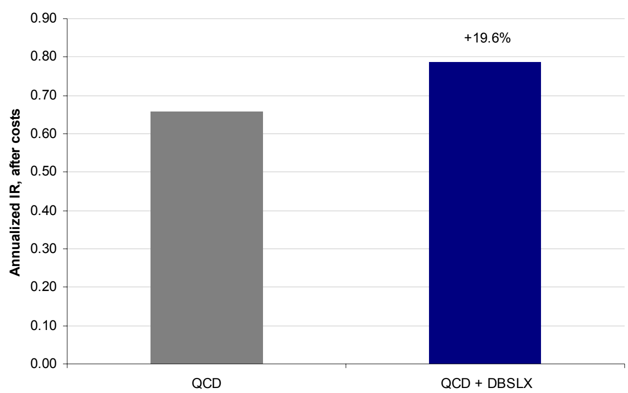
Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Our first simulation is to backtest two optimized portfolios, one a long-short market neutral portfolio and one a long-only portfolio. The long-short portfolio is dollar neutral and targets an annualized risk of 5%. Sector and beta neutrality constraints are used, and turnover is constrained to 20% one-way per month. The long-only portfolio is benchmarked to the Russell 3000 and targets a tracking error of 3%. It also has sector and beta neutrality constraints, and has a turnover constraint of 15% one-way per month. For both portfolios, we charge 20bps of transaction costs for each one-way trade (i.e. we charge this twice for a rebalance). All optimizations are done at a monthly frequency using the Axioma optimizer and the Axioma U.S. Medium-Horizon fundamental risk model. One important point to note is that for the long-only model, we use the composite factor *without* the cost adjustment (i.e. DBSL rather than DBSLX). For the long only investor we of course don't care how expensive a stock is to short; we can avoid these names by underweighting them.

We find the DBSLX factor adds value in a real-world portfolio simulation, both for long-short and long-only investors

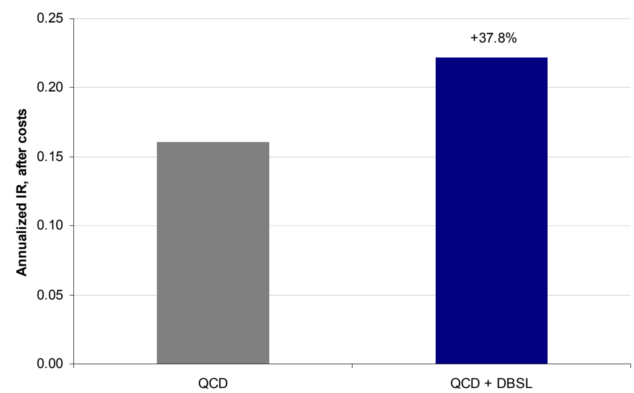
Figure 56 shows the improvement in annualized, after cost information ratio of the long-short portfolio when we include the DBSLX in the alpha signal. The results for the long-only portfolio, using the DBSL factor, are shown in Figure 57. In both cases, adding the new factor does give a quite significant boost in performance. The result in the long-only case is particularly promising. Many quant signals work best when they have the freedom to go long and short, but this particular factor – because of the unique asymmetry in the signal – actually works very well in a long-only context.

Figure 56: Real-world, long-short portfolio simulation, after costs annualized information ratio, 2006-now



Source: Axioma, DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 57: Real-world, long-only portfolio simulation, after costs annualized information ratio, 2006-now, relative to Russell 3000 benchmark



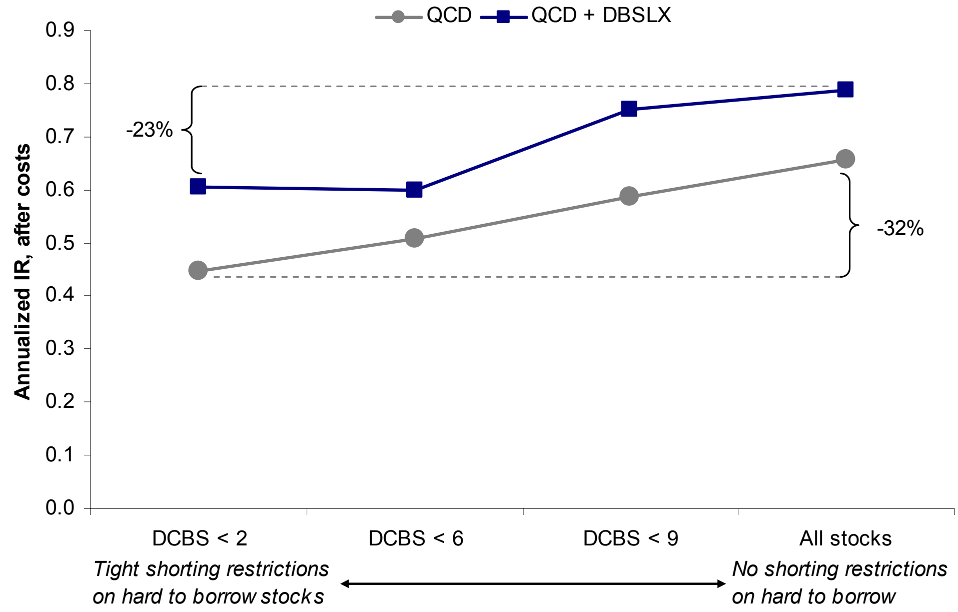
Source: Axioma, DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

These results are promising, but they still gloss over an important point – we still haven't incorporated the cost of borrowing into the portfolio simulations. Even though we use the cost-adjusted DBSLX factor for the long-short portfolio, there is still the chance that the alpha could be eroded once we factor in the cost of trading the short side. As our final test, we rerun the simulation for the long-short portfolio three more times. Each time we put a progressively tighter constraint on the cost of stocks we allow in the short side of the portfolio. Figure 58 shows the results.

Even if we completely avoid all stocks except the cheapest to borrow, we still find the DBSLX factor adds incremental alpha

As expected, when we force the short portfolio to only contain stock from the cheapest to borrow bucket (DCBS = 1), the performance drops significantly for both alpha signals. However, the key result is that regardless of how tight the cost of shorting constraint is, the model that includes the DBSLX factor always outperforms the base case model. This gives us some level of comfort that we can harvest incremental alpha from the factor, even if we face high borrowing costs and a high hurdle rate.

Figure 58: Change in after-cost, risk-adjusted performance when hard to borrow stocks are progressively eliminated from the short portfolio



Source: Axioma, DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Digging deeper

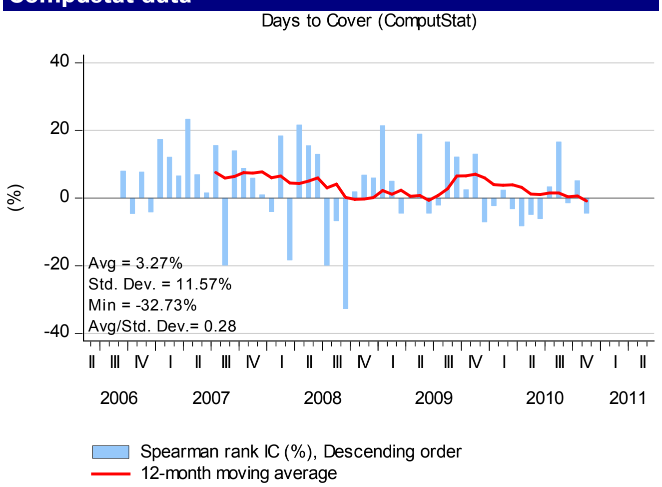
The importance of timing

Having a more timely data source is important

There are a number of points from our study that we think warrant a bit more discussion. One of the most obvious questions arising from our research is whether using the more timely DataExplorer data is actually worth it. As mentioned, most stock exchanges (e.g. the NYSE) provide some level of short interest data, albeit with a significant lag. How much difference does that lag actually make? Figure 59 shows the performance of a simple Days to Cover factor constructed using Compustat data (which is sourced from exchange data). Figure 60 shows the same chart using the DataExplorers data.

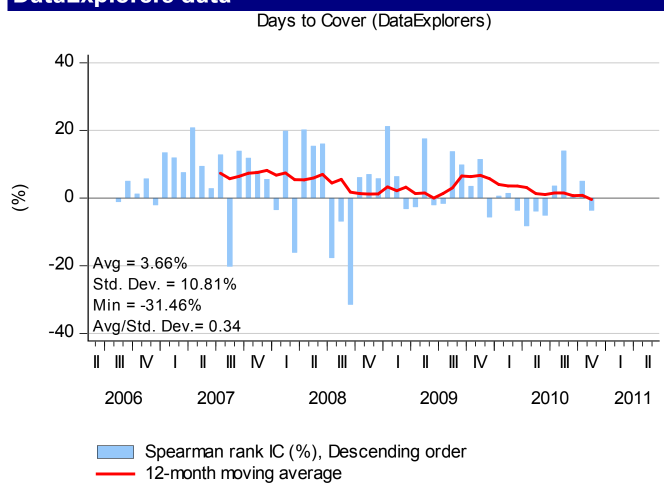
Over the life of the backtest, the DataExplorers data raise the average rank IC of the factor by around 12% in raw terms and 21% in risk-adjusted terms.

Figure 59: Backtest of Days to Cover factor using Compustat data



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 60: Backtest of Days to Cover factor using DataExplorers data



Source: DataExplorers, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

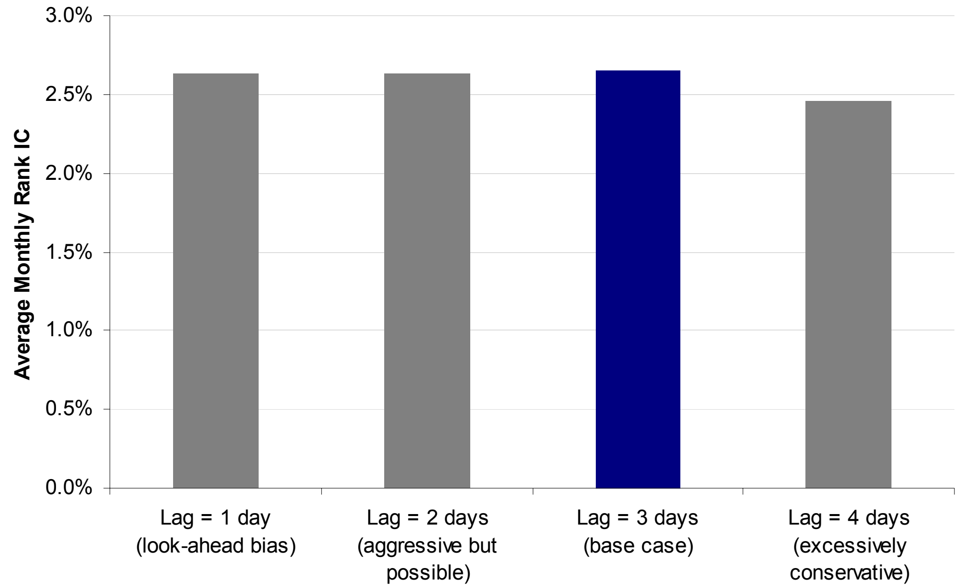
To lag or not to lag

It is important to include a lag when backtesting the DataExplorers data

On the subject of timing, another important point is the question of what lag to apply to the DataExplorer timestamps. The data are delivered via an FTP feed on a t+2 basis, so at a minimum one needs to lag the data by at least two business days. In all the research in this report we take a slightly more conservative approach and use a three-day lag, even though this is more than what is strictly necessary to avoid look-ahead bias. To get a feel for the impact this lag has on our results, we backtest the DBSLX signal with lags ranging from 0 days (major look-ahead bias) to 4 days (extremely conservative).

Overall we find the results actually don't change that much, which is actually not that surprising when we consider the information decay profile of the signal, which was relatively mild.

Figure 61: Average monthly rank IC from backtest of DBSLX, assuming various signal lags



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

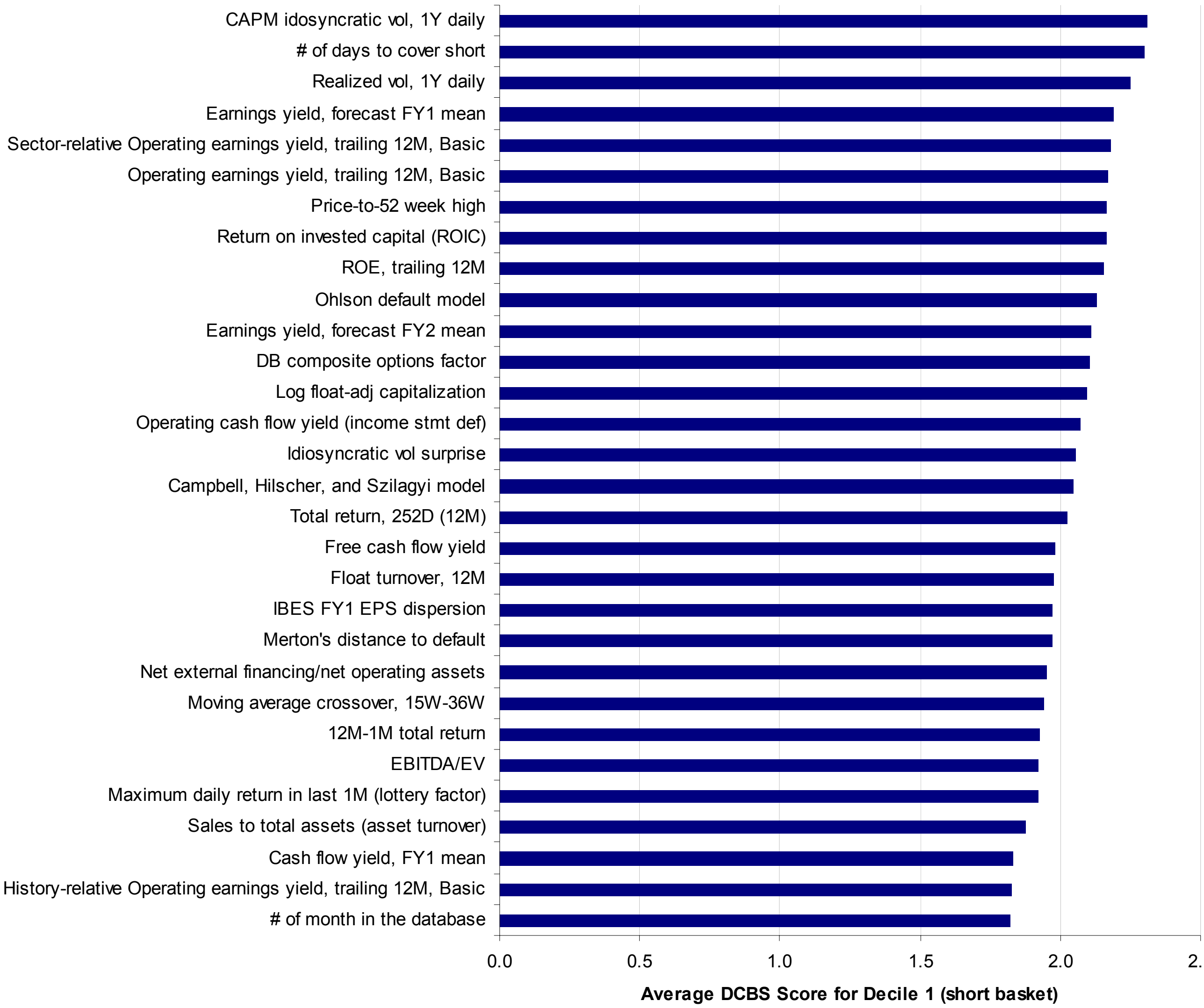
The real cost of factors

We extend our cost analysis to examine the real cost of trading the short side of common quant factors

Outside of building and backtesting factors, stock loan data has other interesting uses. One idea is to use the cost of borrow data to asses how expensive it really is to trade the short side of all our common quant factors. Figure 62 shows the 30 most expensive factors to short, when we rank them based on the average cost of borrow score (DCBS) for the stocks in the short decile portfolio over the backtest period.

Interestingly, volatility factors tend to top the list. Taking a short position in stocks with high idiosyncratic volatility or total volatility is expensive. It is also costly to short stocks that are "expensive" based on earnings yield. In both cases these limits to arbitrage may make it relatively more difficult to fully take advantage of these two anomalies.

Figure 62: Average Cost of Borrow Score (DCBS) for Decile 1 (short basket) for the 30 most costly to borrow factors



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

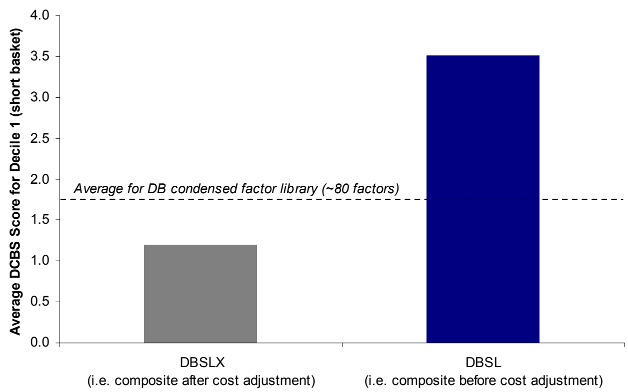
An interesting follow up to this analysis is to ask where the DBSLX factor sits in this ranking. It turns out that because of the cost adjustment that we apply to that factor, it is actually relatively cheap to borrow the short side, both when compared to the overall universe of quant factors (Figure 63) and the average cost of shorting broad quant style composites (Figure 64).

After the cost adjustment, the DBSLX factor is actually cheaper to trade on the short side compared to the average quant factor

This suggests that we could potentially apply our simple cost adjustment regression to all our factors, since many of them have a significant exposure to borrow costs on the short side.[21] Of course, one could also argue that we should leave these types of implementation considerations to the portfolio construction step, and let an optimizer make these tradeoffs instead. Determining which approach is better is an interesting extension for future research.

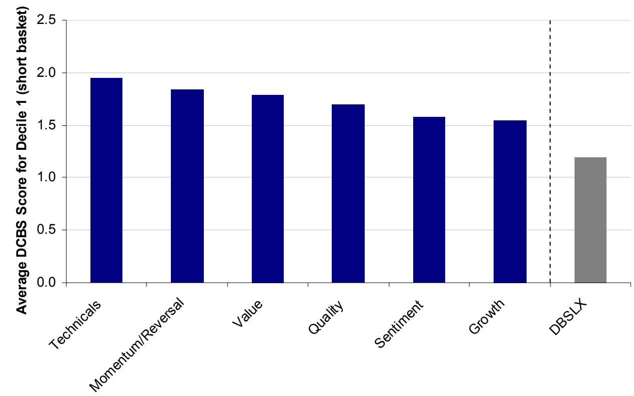
[21] In a sense this is not dissimilar to the approach we took in our factor neutralization research, where we argued that in some cases it is better to make adjustments – in that case for volatility – at the factor level before (or even in place) of optimization. See: Luo, Y., R. Cahan, J. Jussa, and M. Alvarez, 2010, "Portfolios Under Construction: Volatility = 1/N", *Deutsche Bank Quantitative Strategy*, 16 June 2010.

Figure 63: Average Cost of Borrow Score (DCBS) for Decile 1 (short basket) for DBSLX



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 64: Average Cost of Borrow Score (DCBS) for Decile 1 (short basket), by style bucket

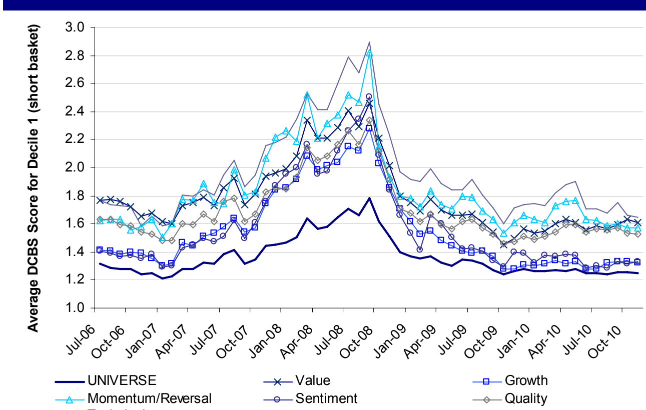


Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Through the credit crisis, the cost of borrowing increased significantly, particularly for quantitative investors

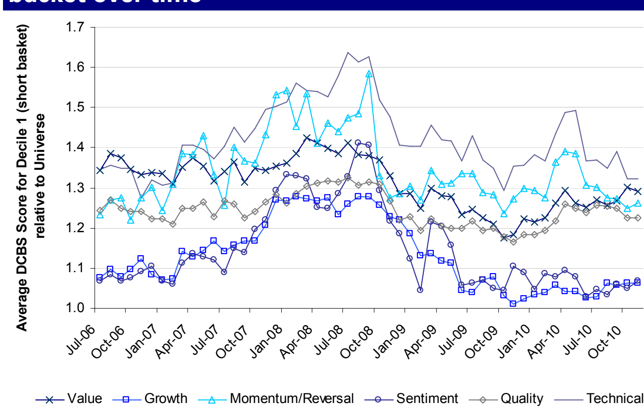
We can also track the cost of factors over time. Figure 65 shows the average cost of the short basket for each of the style composites, plus the average cost of borrow score for the whole universe (the thick blue line). Unsurprisingly, through the financial crisis the cost of borrowing skyrocketed. The jump in borrowing costs, however, disproportionately impacted quant investors. If we look at the cost of shorting factors *relative* to the overall "cost" of the universe (Figure 66), we find that quant borrowing costs climbed more than borrowing costs overall. Perhaps this is because quant strategies on average tend to demand a relatively high level of liquidity, but such liquidity was at a premium through the crisis.

Figure 65: Average Cost of Borrow Score (DCBS) for Decile 1 (short basket), by style bucket over time



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 66: Average Cost of Borrow Score (DCBS) for Decile 1 (short basket) relative to universe, by style bucket over time



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

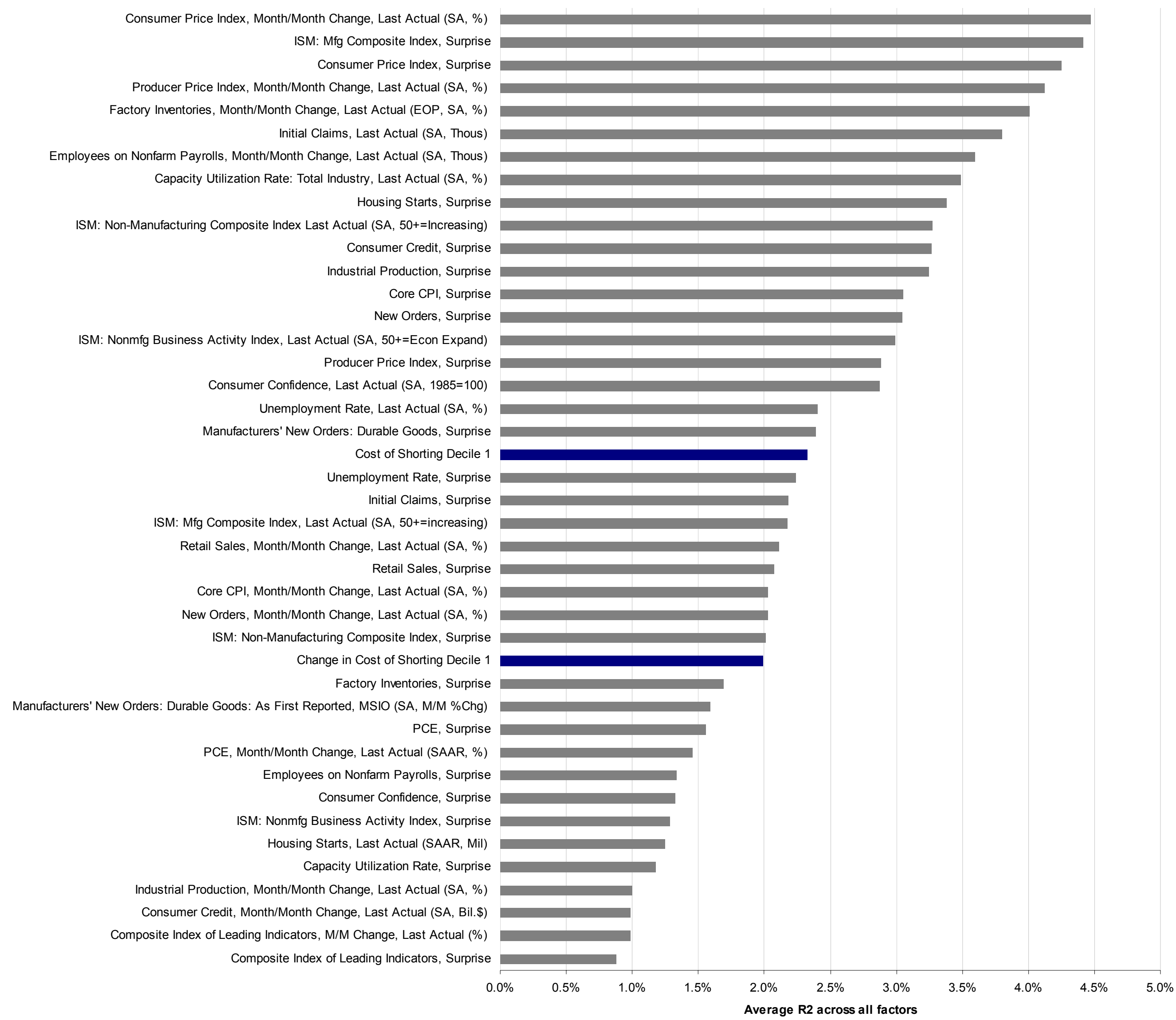
A new style-timing tool?

Another interesting potential use for the stock loan data is to try to use it as a style-timing tool. We have recently done a lot of work on style-timing, and in general found that it can add value, and that macroeconomic type inputs tend to work best in predicting month-ahead factor returns.[22] Can we use the cost of factors to perhaps gauge how crowded a factor is, and potentially whether we should avoid it at certain points in time?

We ask whether we can use the cost of trading the short side of factors a factor timing tool

To test this idea we carry out a simple time-series regression where we regress the average cost of the bottom decile of a factor onto the month-ahead factor return for that factor. We repeat the same exercise with the change in borrow cost. To get a summary statistic, we look at the average R^2 from carrying out these regressions for each of the 80 factors that we commonly track. To put the results in context, we rank them relative to the economic and capital market variables that we considered in our style rotation research (Figure 67).

Figure 67: Average predictive power of style-timing variables in forecasting 1-month ahead factor returns, 2006-present



Note: Average R2 is taken across ~80 quant factors that DB tracks regularly
Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

[22] Luo, Y. R. Cahan, J. Jussa, and M. Alvarez, 2010, "Signal Processing: Style rotation", *Deutsche Bank Quantitative Strategy*, 7 September 2010

Our results for factor timing are disappointing

Unfortunately, while the idea sounded promising, the results are less so. The cost of borrow and change in cost of borrow variables only rank middle-of-the-road in terms of explanatory power in predicting future factor returns. Given these results, we don't pursue this idea further at this stage.

When is a short not a short?

One of the problems with stock borrow data is that the majority of borrowing activity is not associated with a negative view

When talking about stock borrow, we have to this point implicitly assumed that on average investors who short a stock do so because they have a negative view on the stock. In reality there are countless other reasons why we might want to short a stock. Two obvious examples are tax arbitrage and convertible arbitrage.

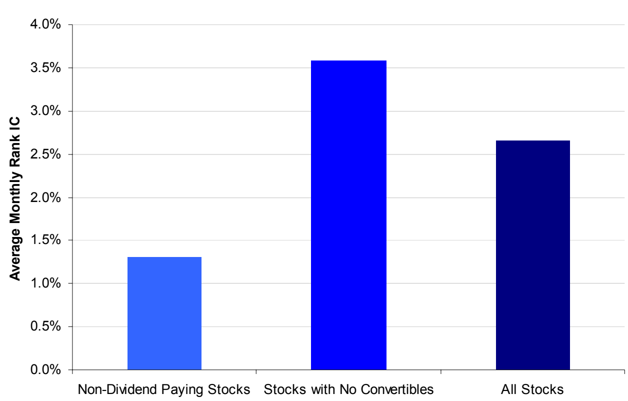
In the former case, the beneficial owner of a security may lend the security, and hence temporarily pass ownership, to someone who may have a more favorable tax situation. The borrower of the security receives the dividend, but then pays the lender a "manufactured" dividend equal to the amount that the lender would have received had they not lent the stock. However, if the borrower has a more favorable tax rate, then the parties can effectively split the difference between the tax the lender would have paid, and the more favorable tax rate the borrower pays on dividends. The point here is that shorting for tax arbitrage does not really represent a negative view on the underlying stock, and hence if this type of borrowing is occurring it may dilute our signal strength. Ancedotally this type of tax arbitrage is not as common in the U.S. as it is in other regions, due to the typically lower dividends paid by U.S. companies. Nonetheless, it is worth doing some quick tests to assess the potential impact of tax arbitrage strategies. We do this in a simple way: we rerun our backtest after excluding all dividend paying stocks.

We try stripping out dividend paying stocks and stocks with convertibles, but don't find a significant improvement in signal efficacy

Convertible arbitrage is a similar story, where an investor may be taking a long position in the convertible and a short position in the underlying equity. Again, the short in this case is not based on any expectation that the stock will decline, it is purely a hedge against the embedded warrant in the convertible. We can test whether this type of arbitrage has any impact by backtesting our factor after excluding all stocks with convertibles trading over them.

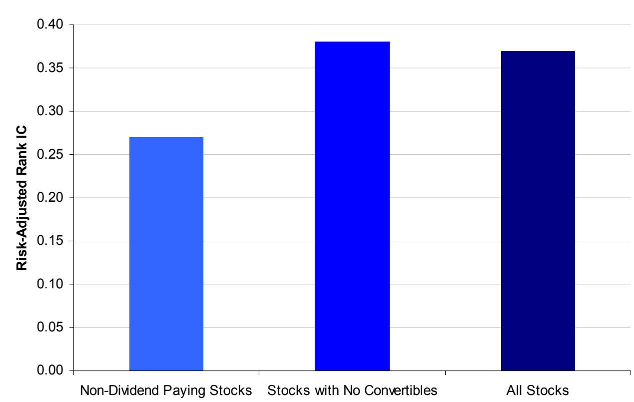
Figure 68 shows the rank IC results, and Figure 69 shows the risk-adjusted results.

Figure 68: Difference in performance of DBSLX when excluding dividend paying stocks and stocks with convertibles



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 69: Difference in risk-adjusted performance of DBSLX when excluding dividend paying stocks and stocks with convertibles



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

The results for the tax arbitrage experiment are clear: eliminating dividend paying stocks actually hurts performance. This is the opposite of what we would expect if tax arbitrage activity was diluting signal efficacy for high dividend payers. However, the case for convertible arbitrage is less clear cut. In raw terms, removing stocks with convertibles helps performance, which supports the view that shorting for convertible arbitrage is muddying the signal strength. On the other hand, the risk-adjusted results are in line with the results for the whole universe. Overall the results suggest we might be able to improve the signal a little by filtering out stocks with heavy convertibles trading.

The problem with trying to strip out shorts that aren't taking a negative view is that it is hard to know where to draw the line

However, as quants we probably know better than anyone that there are many more reasons to short a stock than just having a negative view. For example, in a long-short portfolio we will probably take a number of short positions in stocks purely for risk control reasons, to balance the risk of stocks on the long side of our portfolio. So we could easily take this argument to the extreme and start stripping out stocks with heavy quant trading (perhaps measured by program trading flow), in addition to those with large dividends and those with convertibles. Where would we draw the line? At some point we will end up with no stocks left in our universe. For this reason, while we acknowledge that trying to filter the signal for these considerations makes sense in theory, in practice it is somewhat hard to know when to stop. Instead we take the easy way out and apply no restrictions to our universe, at the expense of a potentially less "pure" signal.

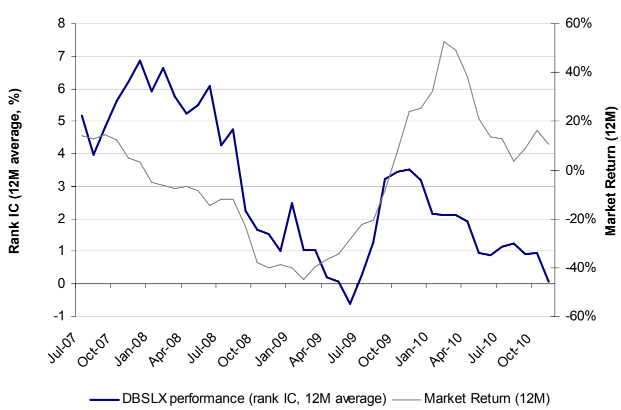
A beta play in disguise?

Our factor appears to be weakly contrarian in that it seems to work better in down markets

Last, but certainly not least, we examine whether there is a potential beta exposure in our DBSLX factor. As we saw in our correlation analysis, there is definitely a cross-sectional correlation with size, which is itself something of a beta proxy (small cap stocks tend to be higher beta). Those results suggested the factor is on average long large cap stocks and short small caps, or long low beta names and short high beta names. This means our factor has the potential to be contrarian – it may work well when the market is falling and struggle when the market is rising. Is this true?

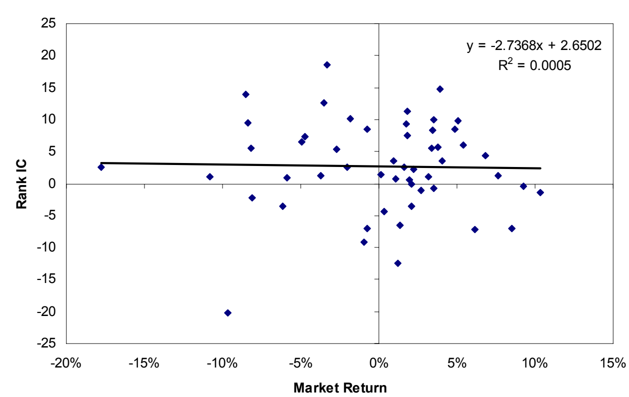
Unfortunately, given the short history it is difficult to draw any solid time-series based conclusions. Eyeballing Figure 70, which shows the performance of the factor overlaid with market returns, it appears that the contrarian argument may be roughly true. Performance of the factor was good as the market dropped into the financial crisis, and then was at its worse when the market rallied sharply through the junk rally around March 2009. However, if we do a scatterplot of monthly factor performance versus monthly market performance, there is no relationship.

Figure 70: 12-month rolling DBSLX performance and market performance



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 71: Monthly DBSLX rank IC versus 1M market return



Source: DataExplorers, Reuters News Analytics, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

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Appendix A: Factor definitions

Figure 72: Factor definitions

Factor	Type	Description
BO Inventory Quantity Add	Adjustment Factors	Quantity of inventory for existing beneficial owners who did not hold stock and now do
BO Inventory Quantity Decrease	Adjustment Factors	Change in quantity of inventory for existing beneficial owners who have decreased their inventory
BO Inventory Quantity Increase	Adjustment Factors	Change in quantity of inventory for existing beneficial owners who have increased their inventory
BO Inventory Quantity New	Adjustment Factors	Quantity of inventory for beneficial owners joining the group
BO Inventory Value Add	Adjustment Factors	Value of inventory for existing beneficial owners who did not hold stock and now do
BO Inventory Value Decrease	Adjustment Factors	Change in value of inventory for existing beneficial owners who have decreased their inventory
BO Inventory Value Increase	Adjustment Factors	Change in value of inventory for existing beneficial owners who have increased their inventory
BO Inventory Value New	Adjustment Factors	Value of inventory for new beneficial owners joining the group
BO On Loan Quantity Add	Adjustment Factors	Quantity of stock on loan for existing beneficial owners who did not lend stock and now do
BO On Loan Quantity Decrease	Adjustment Factors	Change in quantity on loan for existing beneficial owners who have decreased their stock on loan
BO On Loan Quantity Increase	Adjustment Factors	Change in quantity on loan for existing beneficial owners who have increased their stock on loan
BO On Loan Value Add	Adjustment Factors	Value of stock on loan for existing beneficial owners who did not lend stock and now do
BO On Loan Value Decrease	Adjustment Factors	Change in value on loan for existing beneficial owners who have decreased their stock on loan
BO On Loan Value Increase	Adjustment Factors	Change in value on loan for existing beneficial owners who have increased their stock on loan
Broker Demand Quantity Add	Adjustment Factors	Quantity of borrowed stock for existing brokers who did not borrow stock and now do
Broker Demand Quantity Decrease	Adjustment Factors	Change in quantity of borrowed stock for existing brokers who have decreased their borrowed stock
Broker Demand Quantity Increase	Adjustment Factors	Change in quantity of borrowed stock for existing brokers who have increased their borrowed stock
Broker Demand Value Add	Adjustment Factors	Value of borrowed stock for existing brokers who did not borrow stock and now do
Broker Demand Value Decrease	Adjustment Factors	Change in value of borrowed stock for existing brokers who have decreased their borrowed stock
Broker Demand Value Increase	Adjustment Factors	Change in value of borrowed stock for existing brokers who have increased their borrowed stock
DCBS	Borrow Cost	Data Explorers Daily Cost of Borrow Score; a number from 1 to 10 indicating the rebate/fee charged by the agent lender based on the 7 day weighted average cost, where 1 is cheapest and 10 is most expensive
SAF	Borrow Cost	Simple average fee of stock borrow transactions from hedge funds in this security
SAR	Borrow Cost	Simple average rebate of stock borrow transactions from hedge funds in this security
VWAF 1 Day Change	Borrow Cost	Change in the 1 day average fee compared to yesterday's 1 day average fee
VWAF 30 Day Change	Borrow Cost	Change in the 30 day average fee compared to yesterday's 30 day average fee
VWAF 60 Day Change	Borrow Cost	Change in the 60 day average fee compared to yesterday's 60 day average fee
VWAF 7 Day Change	Borrow Cost	Change in the 7 day average fee compared to yesterday's 7 day average fee
VWAF All Change	Borrow Cost	Change in the average fee for all trades compared to yesterday's average fee for all trades
VWAF Score 1 Day	Borrow Cost	Value weighted average fee for all new trades on the most recent day expressed in undisclosed fee buckets 0-5, where 0 is the cheapest to borrow and 5 the most expensive
VWAF Score 30 Day	Borrow Cost	Value weighted average fee for all new trades on the most recent 30 calendar days expressed in undisclosed fee buckets 0-5, where 0 is the cheapest to borrow and 5 the most expensive

Source: DataExplorers, Deutsche Bank

Figure 72: Factor definitions (Continued)

Factor	Type	Description
VWAF Score 60 Day	Borrow Cost	Value weighted average fee for all new trades on the most recent 60 calendar days expressed in undisclosed fee buckets 0-5, where 0 is the cheapest to borrow and 5 the most expensive
VWAF Score 7 Day	Borrow Cost	Value weighted average fee for all new trades over the most recent 7 calendar days expressed in undisclosed fee buckets 0-5, where 0 is the cheapest to borrow and 5 the most expensive
VWAF Score All	Borrow Cost	Value weighted average fee for all trades expressed in undisclosed fee buckets 0-5, where 0 is the cheapest to borrow and 5 the most expensive
Active Available BO Inventory Ratio	Demand	Active available quantity divided by 21 day average cash equity trading volume
Active Brokers	Demand	Number of brokers with open transactions
Active Utilization	Demand	Demand value as a % of the realistically available supply (BO On Loan Value / Active BO Inventory Value)
Active Utilization by Quantity	Demand	Demand quantity as a % of the realistically available supply (BO On Loan Quantity / Active BO Inventory Quantity)
BO Inventory Value Concentration Ratio	Demand	A value between 0 and 1 to measure the distribution of inventory, where a very small number indicates a large number of lenders and 1 indicates a single lender with all the inventory. 0 means there is no inventory for the stock. Derived from a concentration measure based on the sum of squared market shares
BO Inventory Value Rank 1 Market Share	Demand	Relative to the total value of BO Inventory, the % held by the lender with the biggest market share
BO Inventory Value Rank 2 Market Share	Demand	Relative to the total value of BO Inventory, the % held by the lender with the second biggest market share
BO On Loan Quantity	Demand	Quantity of current inventory on loan from beneficial owners
BO On Loan Value	Demand	Value of current inventory on loan from beneficial owners
BO On Loan Value Concentration Ratio	Demand	A value between 0 and 1 to measure the distribution of lender value on loan, where a very small number indicates a large number of lenders and 1 indicates a single lender with all the value on loan. 0 means there is no value on loan for the stock. Derived from a concentration measure based on the sum of squared market shares
BO On Loan Value Rank 1 Market Share	Demand	Relative to the total value of BO On Loan, the % lent by the lender with the biggest market share
BO On Loan Value Rank 2 Market Share	Demand	Relative to the total value of BO On Loan, the % lent by the lender with the second biggest market share
Broker Demand Quantity	Demand	Quantity of current securities borrowed by brokers. NOTE this field is not the full demand picture. Use Total Demand
Broker Demand Value	Demand	Value of current securities borrowed by brokers. NOTE this field is not the full demand picture. Use Total Demand
Broker Demand Value Concentration Ratio	Demand	A value between 0 and 1 to measure the distribution of broker demand, where a very small number indicates a large number of active brokers and 1 indicates a single active broker. 0 means there is no broker demand for the stock. Derived from a concentration measure based on the sum of squared market shares
Broker Demand Value Rank 1 Market Share	Demand	Relative to the total value of Broker Demand, the % borrowed by the broker with the biggest market share
Broker Demand Value Rank 2 Market Share	Demand	Relative to the total value of Broker Demand, the % borrowed by the broker with the second biggest market share
Change in Short Interest, 1M	Demand	One month change in Short Interest
Change in Utilization, 1M	Demand	One month change in Active Utilization
Days to Cover (ComputStat)	Demand	Total Demand Quantity / Average Daily Volume
Days to Cover (DataExplorers)	Demand	Shares Sold Short (from Compustat, snapped 15th of the month) / Average Daily Volume
Open Loan Transactions	Demand	Total number of open transactions from Beneficial Owner side only. Custodians typically report a separate transaction for every underlying Beneficial Owner or fund from who the borrow is taken
Short Interest	Demand	Total Demand Quantity / Shares on Issue
SL Tenure	Demand	The weighted average number of days from start date to present for all open transactions
Total Demand Quantity	Demand	Total quantity of borrowed/loaned securities net of double counting
Total Demand Value	Demand	Total value of borrowed/loaned securities net of double counting

Source: DataExplorers, Deutsche Bank

Figure 72: Factor definitions (Continued)

Factor	Type	Description
Utilization	Demand	The value of assets on loan from beneficial owners (BO On Loan Value) divided by the total lendable assets (BO Inventory Value), expressed as a percentage. For Record Type 2 this value is implied
Utilization by Quantity	Demand	Utilization calculated using quantity rather than value figures (BO On Loan Quantity / BO Inventory Quantity)
DIMV	Indicator	Data Explorers Increased Market Volatility gives high scores to securities that have a high DNS and a high DIPS. With high short interest and a good chance of being a squeeze one can expect short term price volatility in such names and seek to profit from this.
DIPS	Indicator	Data Explorers Increasing Price Squeeze indicator compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. A DIPS of greater than 20% is considered high
DNS	Indicator	Data Explorers Negative Sentiment indicator shows the change in the average BO inventory quantity (longs) in relation to the average total demand quantity (shorts) for the security. The scale for this indicator is from 0% to 100%. A high DNS generally reflects negative sentiment (an increasing amount of shorts relative to longs) while a low number shows relatively less negative sentiment
DPS	Indicator	Data Explorers Positive Sentiment gives higher scores to securities with low and unchanging utilization
DSS	Indicator	Data Explorers Short Score is a simple score from 0 to 5 based upon the total demand as a % of the shares outstanding. 0 is a proxy for low short interest, 5 is high. The buckets are fixed regardless of country
Active Agents	Supply	Number of custodians and lending agents with open transactions
Active Available BO Inventory Quantity	Supply	Quantity of shares realistically available for borrowing by removing BO On Loan Quantity from Active BO Inventory Value
Active Available BO Inventory Value	Supply	Value of shares realistically available for borrowing by removing BO On Loan Value from Active BO Inventory Value
Active BO Inventory Quantity	Supply	As above but expressed in shares not value
Active BO Inventory Value	Supply	Current inventory available from beneficial owners less what is deduced to be temporarily restricted from lending, e.g., where securities are held in too small parcels or have been restricted by the beneficial owners (see the FAQs for details of the methodology)
BO Inventory Quantity	Supply	Quantity of current inventory available from beneficial owners. For record type 2 this value is implied
BO Inventory Value	Supply	Value of current inventory available from beneficial owners. For record type 2 this value is implied
Change in Supply, 1M	Supply	Change in Short Interest
Inactive Agents	Supply	Number of custodians and lending agents with inventory but without open transactions
Percent of Shares Available for Borrow	Supply	Active Available BO Inventory Quantity / Shares on Issue

Source: DataExplorers, Deutsche Bank

Appendix 1

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