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Uncovering hidden economic links

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Extracting alpha from economically-linked companies

In this report we use a unique database of company-level economic relationships to build a stock-selection model. Our model, which we call the QLINK model, identifies clusters of economically-related stocks and then uses a statistical model within each cluster to forecast future returns.

Understanding a hyperlinked world

Today's global supply chains are incredibly complex; just think how many companies are involved in delivering one smartphone to a customer. Sometimes a flood in Thailand or a volcano in Iceland will reveal these hidden links, but most of the time they slip by unnoticed. Until now…

Introducing a unique database of company-level relationships

In this research we introduce a unique database that captures the complex network of relationships between individual companies. For example, we can use the data to identify a firm's customers, suppliers, competitors, and so on. This can be a powerful ingredient to add to a quantitative model.

All together now

Our QLINK model recognizes that firms do not operate in isolation. Instead, the returns of economically-linked firms are inextricably tied together, often in a way that is not obvious to the naked eye. By using statistical techniques we find there is often alpha to be had in these hidden links.

Deutsche Bank Securities Inc.

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A letter to our readers

Uncovering hidden economic links

Take a look at that smartphone in your pocket. How many companies played a part in getting it to you in a nice shrink-wrapped box? Someone had to dig up the rare earth metals used in the circuit board capacitors. Someone else had to supply the glass for the screen. Then those parts, plus thousands of other components from all over the world, had to be painstakingly assembled somewhere. But it doesn't end there. A logistics company had to coordinate the shipping to make sure the right amount of inventory got to the right place at the right time; a network carrier had to sell you the phone; an advertising agency designed the catchy ad that made you buy it in the first place; the list goes on. And when you buy a case to protect all that hard work, you've added yet another company to the list.

It goes without saying that today's global supply chains are complex. Usually, when things are working, the carefully orchestrated dance of suppliers and customers slips by unnoticed. But when things go wrong it's a different story. A flood in Thailand, a snowstorm in New York, or a dry winter in New Zealand can ripple across the world very quickly in today's hyperlinked economy. How can we hope to ever comprehend such a complicated world?

A data driven approach

Fortunately, as quants, we can turn to the data. In this report we use a unique database of company-level relationships, from a company called Revere Data LLC, to help us understand the economic links between companies. The database captures publicly disclosed relationships between companies, allowing us to identify firms that are related as customers, suppliers, competitors, and so on. Using these relationships, we can identify clusters of economically-related stocks, which are not necessarily in the same sector or indeed even the same country. Our hypothesis is that the stock price returns of firms in a cluster are more likely to be linked, given the real-world business relationships between the companies.

We show that a Vector Autoregressive (VAR) model is a natural way to model the relationship between stocks in an economic cluster. The VAR model allows the future returns of stocks in the cluster to depend not just on their own past performance (i.e. momentum and reversal) but also the past performance of other stocks in the cluster. The advantage of the VAR model is that it does not impose a prior view on how performance should propagate along the supply chain.

For example, most of the academic literature in the space has focused on customer momentum, i.e. buy the stocks whose customers are doing well, and sell the stocks whose customers are doing poorly. In contrast, the VAR model allows for more complex relationships. For example, what should happen if the competitor of a firm is doing well? Maybe this is a bad sign, because it means the firm will lose market share to the competitor. Or maybe it is a positive signal, because the whole industry is booming and both companies can do well. To find out the answers, read on.

Regards,

Yin, Rocky, Miguel, Javed, John, and Sheng
Deutsche Bank Quantitative Strategy

Identifying economic links

Introducing the Revere database

In this research we use a unique database of company-level relationship data provided by a firm called Revere Data LLC. The company specializes in collecting publicly disclosed information about a company's network of customers, suppliers, competitors, and geographic exposures. The data points are collected continuously and mapped to a consistent taxonomy to make querying the data and comparing companies easier.

Company relationships

The Revere database consists of a number of modules. The one we will use most extensively in this report is the Company Relationships module. This database captures detailed company-level relationships between firms in a point-in-time format. For example, Figure 1 shows some of the relationships for Apple (AAPL) as at 28 February 2013. In this example, most of the related companies are suppliers, but there is one customer, AT&T (T). Of course, this is just a small snapshot of the data available; currently AAPL has over 150 related companies listed in the database. It is also important to note that the related companies are not limited to listed companies: some of the companies are private (see the names with no ticker symbol below). The database also included non-US companies, for example in this particular snapshot a Taiwanese supplier and an Austrian supplier show up.

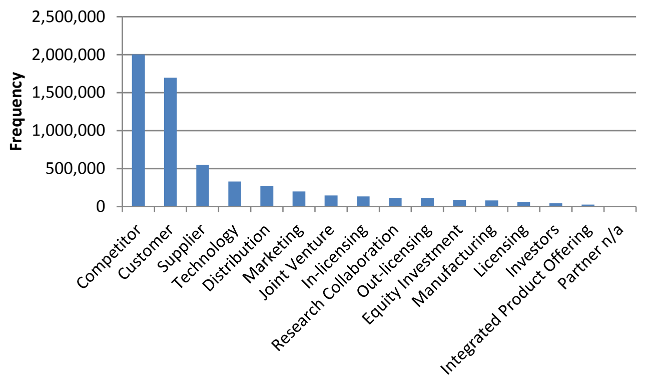
Figure 1: Sample Companies related to AAPL, as at 28 February 2013

POINTDATE	SOURCE_COMPANY_NAME	SOURCE_COMPANY_TICKER	REL_TYPE	TARGET_COMPANY_NAME	TARGET_COMPANY_TICKER
28-FEB-13	Apple Inc	AAPL	Supplier	AAC Technologies Holdings Inc	AACAY
28-FEB-13	Apple Inc	AAPL	Supplier	AT & S Austria Technologie & Systemtechnik AG	ATS:AT
28-FEB-13	Apple Inc	AAPL	Customer	AT&T Inc	T
28-FEB-13	Apple Inc	AAPL	Supplier	AU Optronics Corp	AUO
28-FEB-13	Apple Inc	AAPL	Supplier	AcBel Polytech Inc	6282:TW
28-FEB-13	Apple Inc	AAPL	Supplier	Acument Global Technologies, LLC	(null)
28-FEB-13	Apple Inc	AAPL	Supplier	Advanced Micro Devices Inc	AMD
28-FEB-13	Apple Inc	AAPL	Supplier	Amperex Technology Ltd.	(null)
28-FEB-13	Apple Inc	AAPL	Supplier	Amphenol Corporation	APH
28-FEB-13	Apple Inc	AAPL	Supplier	Analog Devices Inc	ADI
28-FEB-13	Apple Inc	AAPL	Supplier	Anjie Insulating Material Co., Ltd.	(null)
28-FEB-13	Apple Inc	AAPL	Supplier	Asahi Kasei KK	AHKSY

Source: Revere Data

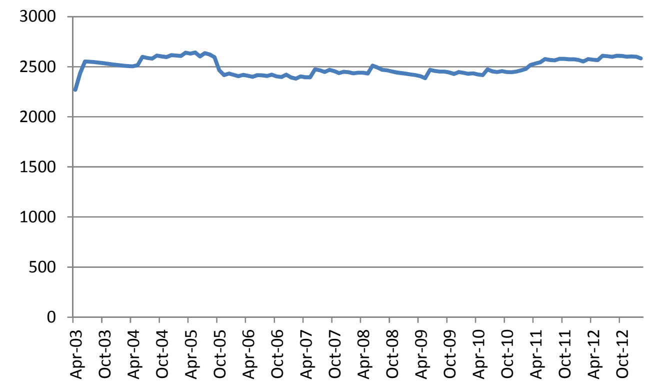
Figure 2 shows the different types of relationships captured in the Revere database, along with their frequency (based on the Russell 3000 universe from 2003-present). The three most common relationships are Competitor, Customer, and Supplier relationships.

Figure 2: Frequency of relationship types for Russell 3000 stocks, 2003-present



Source: Revere Data, Russell, Deutsche Bank

Figure 3: Number of stocks in Russell 3000 that have at least one related company



Source: Revere Data, Russell, Deutsche Bank

In terms of coverage and history, the database is quite extensive. In Figure 3 we show the number of stocks in the Russell 3000 that have at least one related company at each point in time. On average around 2,500 stocks are covered. The database starts in April 2003.

Non-company relationships

In addition to company-to-company relationships, the database captures relationships to other entities. For example, given the government's propensity to skirt dangerously close to rather precipitous fiscal cliffs, a common question is: which stocks have exposure to US government spending (or rather, lack of spending)? Figure 4 shows that such a list is easily obtained from the Revere database.

Figure 4: Sample companies that are direct suppliers to the US government

SUPPLIER_ID	SUPPLIER_NAME	CUSTOMER_ID	CUSTOMER_NAME
3182	Digital Power Corporation	20685	Government - United States
1832532	The Vitec Group PLC	20685	Government - United States
194512231	API Technologies Corp	20685	Government - United States
9257	Paragon Technologies	20685	Government - United States
6664	Meritor Inc	20685	Government - United States
10625	United Technologies Corp	20685	Government - United States
1680050	Telephone Instrument Electronics Corp	20685	Government - United States
1726629	G4S PLC	20685	Government - United States
249198	Dynasil Corporation Of America	20685	Government - United States
1478913	Sanofi	20685	Government - United States

Source: Revere Data

Geographic segment data

Another common request we get is: give me the list of companies with revenue exposure to Europe. Such data is typically difficult to come by, because even though many companies report geographic segment data, they are free to define their regions however they want. For example, one company might report revenues for US/Canada/Europe/Asia while another might use North America/UK/Europe/Australasia. The Revere Geographic Exposure module captures these reported geographic exposures and maps them to a consistent hierarchy of regions and countries. For example, Figure 5 shows the current revenue exposures for General Electric (GE) with respect to some of the Revere regions and countries. The VALUE column gives the percent of revenue coming from each country/region.

Figure 5: Reported geographic revenue exposure of GE, as at 28 February 2013

NAME	TICKER	HOME_REGION	REGION	VALUE
General Electric Co	GE	US	AMERICAS	56.7322
General Electric Co	GE	US	US	47.7745
General Electric Co	GE	US	EUROPE	18.594
General Electric Co	GE	US	ASIAPAC	16.6261
General Electric Co	GE	US	MIDDLE_EAST_AFRICA	8.0477
General Electric Co	GE	US	SD	0.1221

Source: Revere Data

In the rest of this research, we will delve into ways to use the Revere data in a systematic stock selection model.

Literature review

Before diving into our research, it is worth reviewing what has been done in the space so far. Those of you who are regular readers of our monthly "Academic Insights" paper will know that this is a space that has been getting a lot of attention recently. Some of the key papers are listed below.

Academic research

- **Cohen and Frazinni [2008]** – This seminal paper studies return predictability across economically-linked firms (e.g. customers-suppliers). The authors find that a strategy of buying firms whose *customers* had top quintile returns last month and selling those with bottom quintile returns generates abnormal returns of around 1.55% per month. They hypothesizes that this is due to investor inattention, whereby investors are slow to recognize the new information about a company contained in the performance of its customer base.
- **Shahrur, Becker, and Rosenfeld [2010]** – This paper extends the work of Cohen and Frazinni [2008] to international stocks, using industry-level customer-supplier links from US companies as a proxy for global links. Similar to what to Cohen and Frazinni found for US stocks, the authors of this paper find that suppliers whose customers have been doing well tend to outperform those whose customers have been doing badly. After transaction costs the spread portfolio delivers around 7.2% annually.
- **Rizova [2010]** – The author studies lead-lag relationships in the returns of countries that are linked through trade relationships (e.g. major import and export partners). Specifically, the results show that the past performance of a country's major trade partners positively predicts stock returns in that country, above and beyond the momentum of the country itself. A trading strategy based on this phenomenon yields around 1.2% per month in abnormal returns.
- **Nguyen [2012]** – This paper uses geographic segment data to study whether the market promptly prices changes in foreign market conditions to which a company has revenue exposure. The author shows that a simple strategy that buys stocks that are exposed to countries that have been outperforming, and sells those exposed to underperforming countries, can generate an excess return of around 1.35% per month.
- **Li, Richardson, and Tuna [2012]** – This paper is closely related to Nguyen [2012] in that it examines lead-lad relationships between firms and the countries in which they do business (based on geographic exposure data disclosed by the company). However, unlike Nguyen who mainly uses the past performance of each country's equity market as the explanatory variable, this paper uses

forecasts of the future performance of each region, for example the OECD Leading Indicators.

- **Ahern [2012]** – This research follows a different methodology from the more established supply chain (at the company level) or trade flow (at the country level) methodologies in the previous papers. Instead the author uses a novel measure of how central an industry is in a network of intersectoral trade. He finds that industries that are more central earn higher returns (around 1.1% per month) than those that are not, and argues that this is because these central industries are more exposed to idiosyncratic shocks that propagate from one industry to another via trade.

Deutsche Bank research

- **Mesomeris, Salvini, and Kassam [2010]** – In this research we studied how trade links between countries, extracted from the IMF's Direction of Trade Statistics (DOTS) database, can be used to predict country-level equity returns. We found that there is a lead-lag effect between trading partners, and proposed a strategy where we buy countries whose trading partners are outperforming (measured using their past equity market returns) and sell countries whose trading partners are underperforming.

- **Salvini, Mesomeris, Avettand-Fenoel, and Wang [2012]** – In Europe we studied alpha models based on both business segment and geographic momentum. We also showed how these two strategies are complementary, and can be combined to generate attractive risk-adjusted performance within European equities.

Introducing the QLINK model

A quantitative model of economic linkages

The basic idea behind an economic-linkage model is that the past performance of economically-related companies (or geographic regions) is predictive of future performance. However, in most of the literature to date, researchers have focused on the *momentum* of related entities. For example, Cohen and Frazinni [2008], Shahrur, Becker, and Rosenfeld [2010], Nguyen [2012], and Rizova [2010] all propose models that buy stocks (or countries) whose related entities (e.g. customers, geographic regions, etc.) have been outperforming and sell stocks whose related entities have been underperforming.

Having said this, one can easily imagine scenarios where the relationship between a company's performance and that of its related entities is more complex. For example, suppose a company, ABC, is in a competitive duopoloy with a competitor, XYZ. Now suppose that the competitor XYZ is struggling (i.e. its past returns are negative). In that case, it is certainly possible that ABC will eventually underperform, too; perhaps there are industry-wide headwinds that impact all companies in that sector. In that case the simple momentum model would work well. But is it not equally plausible that the travails of XYZ will be favorable for ABC? Perhaps it will now be able to take market share from its fierce competitor and lift margins?

The Vector Autoregressive (VAR) model is a natural choice

With this is mind, the rich economic relationship data provided by Revere lends itself to a more general model. Instead of assuming a momentum-based model, perhaps we can do better with a model that can capture other, more complicated relationships between past and future returns. An obvious candidate is a Vector Autoregressive (VAR) model. We've used such a model before in our work on country rotation (see Mesomeris et al. [2010]) where we found it can be useful in modeling the return relationships between countries linked through trade flow.

The basic idea of the VAR model is that the return of a stock today, $r_{i,t}$, depends not just on the stock's own past returns, $r_{i,t-1}$, $r_{i,t-2}$, …, $r_{i,t-p}$, but also on the past returns of other stocks, $r_{j,t-1}$, $r_{j,t-2}$, …, $r_{j,t-p}$. More mathematically, we write

$$
\begin{aligned}
r_{1,t} &= c_1 + a_{1,2}^{1} r_{1,t-1} + a_{1,2}^{1} r_{2,t-1} + \cdots + a_{1,k}^{1} r_{k,t-1} + \cdots + a_{1,1}^{p} r_{1,t-p} + a_{1,2}^{p} r_{2,t-p} + \cdots + a_{1,k}^{p} r_{k,t-p} + e_{1,t} \\
r_{2,t} &= c_2 + a_{2,1}^{1} r_{1,t-1} + a_{2,2}^{1} r_{2,t-1} + \cdots + a_{2,k}^{1} r_{k,t-1} + \cdots + a_{2,1}^{p} r_{1,t-p} + a_{2,2}^{p} r_{2,t-p} + \cdots + a_{2,k}^{p} r_{k,t-p} + e_{2,t} \\
&\vdots \\
r_{k,t} &= c_k + a_{k,1}^{1} r_{1,t-1} + a_{k,2}^{1} r_{2,t-1} + \cdots + a_{k,k}^{1} r_{k,t-1} + \cdots + a_{k,1}^{p} r_{1,t-p} + a_{k,2}^{p} r_{2,t-p} + \cdots + a_{k,k}^{p} r_{k,t-p} + e_{k,t}
\end{aligned}
$$

where we have k stocks and believe that the current returns of those stocks depend on p lags of past returns (called the *order* of the model).

How might we apply this model to stock selection? We propose the following algorithm, which we will call our Quantitative Economic Linkages model, or QLINK for short:

1. For a date, t, collect the Revere relationship data as at that point in time.

2. For a stock, i, identify all the other companies (both US and international) that are related to that company. We will call stock i the *source* company, and the related companies the *target* companies.

3. Collect the market-adjusted returns for the source company and all the target companies at that point in time, using a trailing window of T months. The returns are adjusted relative to an equally-weighted index of their home market.[1]

4. Build a monthly VAR model of order p, using the past T monthly, market-adjusted returns of the source company and the target companies. Use this model to predict the month-ahead returns to the source company and all target companies.

5. Z-score the return forecasts from the VAR model in step 4 and save them.

In essence, the algorithm is designed to first identify stocks within what we will call an *economic cluster*. Such a cluster is a group of stocks that are linked together by one of the relationship types captured by Revere (e.g. customer, supplier, competitor, etc.). Once we have that cluster, the VAR model tries to capture the interrelationship of returns within that cluster. Because of step 5, stocks are effectively ranked *within* their economic cluster, rather than relative to the whole universe; this is designed to help overcome the issue of comparability of the return forecasts across different economic clusters.

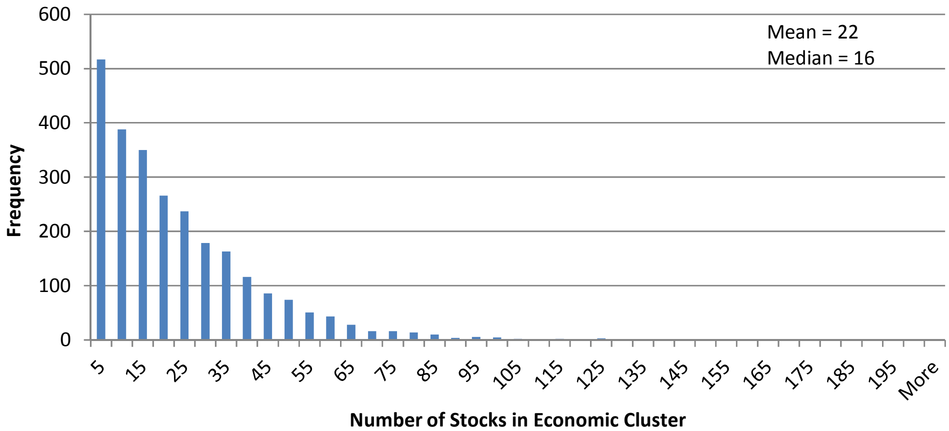
Dimensionality reduction

A few steps in the algorithm warrant further elaboration. First, a major problem with the VAR model in financial applications is dimensionality. Suppose we set the lookback window T to be 10 years; since we are using monthly data this yields 120 data points. Further, suppose we set $p=12$, i.e. we want the return this month of each stock to depend on the past 12 month returns for the stock itself, as well as the past 12 monthly returns of all other stocks in the cluster. Now consider Figure 6. This shows a distribution of the number of stocks in each identified cluster, as of 28 February 2013.

At this point in time, the average economic cluster has 22 stocks, with a median of 16. This is clearly a problem, because it implies for the average cluster we have to estimate over 12 x 22 x 22 = 5,808 coefficients, assuming we want 12 lags in the model. Needless to say, with a time-series of 120 data points this is going to be impossible. Therefore, we need some way of reducing the dimensionality of the problem.

[1] For example, if the source company has two target companies at time t, say one from the US and one from Germany, then the returns of the US stock are adjusted relative to an equally-weighted index of US stocks, and the German stock is adjusted relative to Germany. By definition the source company is adjusted relative to the US, since it will always be a US stock. Also note that because the US market is the last to close, there is no lookahead bias in using past monthly returns of stocks in other countries to predict US stock returns.

Figure 6: Distribution of cluster size, as at 28 February 2013



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

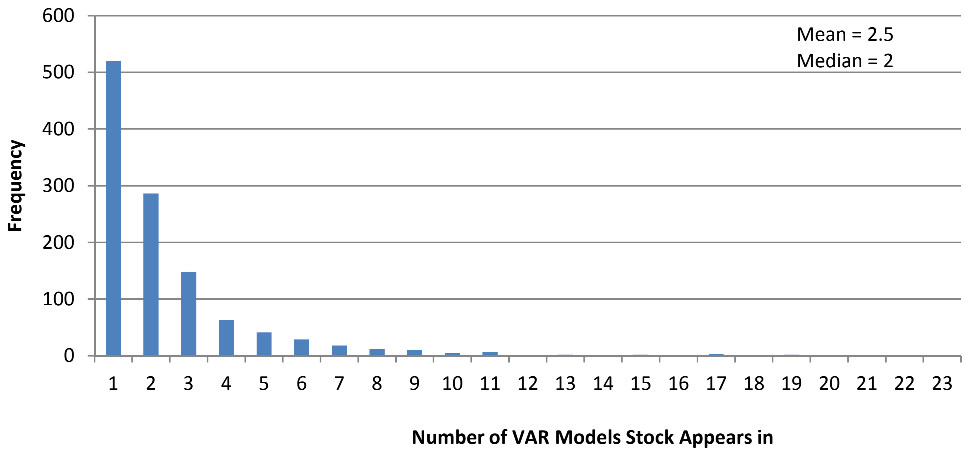
Our approach is to incorporate a statistical pre-processing filter into step 4. Instead of fitting a VAR model to all stocks in the economic cluster, we first run a series of two-stock VAR models with the source stock and each target stock in turn. For each of these models, we record the R-squared of the model in explaining the returns of the source company. Then, for the overall VAR model, we take only the first m target stocks, based on the R-squared from the two-stock VAR models. This ensures that the stocks used in the main VAR model have high predictive power for at least the returns of the source company, before they can be considered candidates for the main VAR model. Later in this report we will discuss how we set m .

Built-in error reduction

Even with the pre-processing step, there are still challenges with the model. Returns are hard to predict, so fitting a complicated VAR model risks overfitting to the inherent noise in returns. This is particularly challenging if we seek to use more lags (i.e. higher values of p). However, the setup of our model does help to dampen down overfitting for the following reason: the forecast return for most stocks will the average forecast across all the clusters that the stock appeared in. For example, a manufacturer that makes, say, electronics components that are used in smartphones will appear in many different economic clusters, depending on how many customers buy its products. It will also appear in other clusters based on its competitors, and so on. For each of those clusters, we will have a forecast return (or more specifically a z-score of the forecast return) for that stock. We average across all forecasts for a given stock at a given point in time to get the final forecast for that stock. Therefore, while a single VAR model can be very noisy, the actual forecast for each stock is the average of a number of different VAR models. As long as the noise is random, this should help dampen some of the error.

Figure 7 shows the distribution of the number of forecasts for each stock, at a particular point in time, in this case 28 February 2013. On average, each stock's forecast is the average forecast across 2.5 different VAR models.

Figure 7: Distribution of number of forecasts for each stock in model, as at 28 February 2013



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

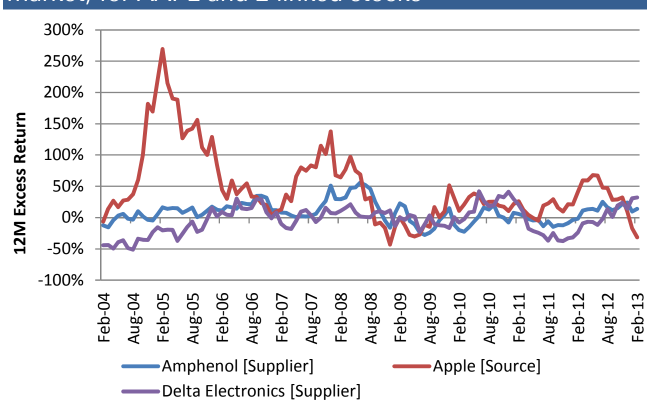
A simple example

Our analysis up to now has been fairly abstract, so let's take a look at a more real-world example. Let's assume we want to run our QLINK model with a lookback of 10 years, 12 lags in the VAR model, and a maximum of two stocks plus the source stock (i.e. $T = 120$, $p = 12$, $m = 2$) as of 28 February 2013. We will use Apple (AAPL) as an example (i.e. AAPL is the source company). In the raw data, AAPL has over 150 relationships captured in the Revere database at that date, however the pre-processing algorithm will cut the final model down to just three stocks, AAPL plus two other names.

It turns out in this case the two target companies the model selects are Amphenol (APH), a US-based manufacturer of electronic connectors, and Delta Electronics (DELTA TB), a diversified electronics manufacturer from Thailand. According to Revere, both were suppliers of AAPL as at 28 February 2013.

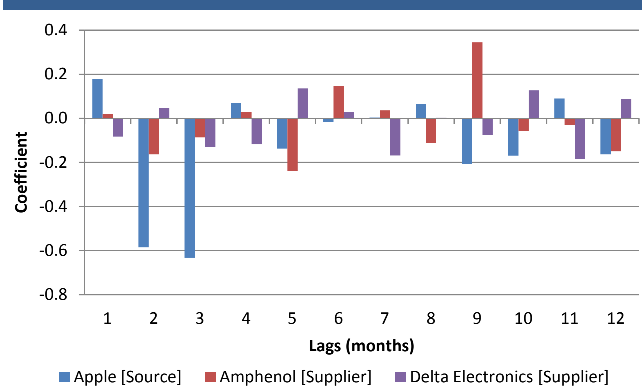
Figure 8 shows the rolling 12-month returns for these three stocks over the 10 years that the model was estimated over. Clearly there is some correlation at times, but the relationship does not appear to be as simple as a pure lead-lag relationship. This is confirmed by examining the coefficients from the model in Figure 9.

Figure 8: 12M rolling performance (relative to home market) for AAPL and 2 linked stocks



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

Figure 9: VAR coefficients for AAPL



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

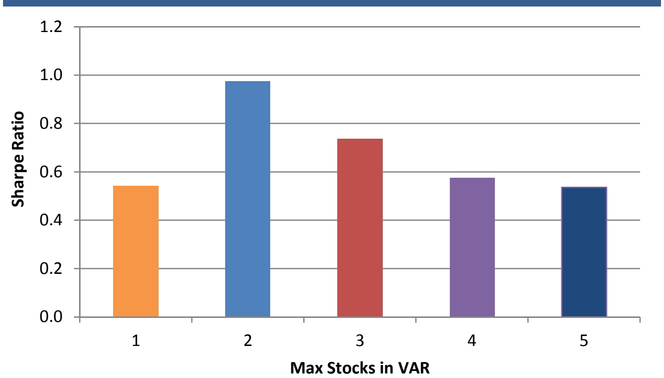
The blue bars show how past returns of AAPL are related to its current month return. Interestingly, at a one month lag there is a moderate momentum effect, but at two and three month lags this becomes reversal (i.e. if the stock was up 2-3 months ago then we expect it to be more likely to be down this month). The red and purple bars show how past returns of APH and DELTA are related to AAPL's current month return.

From the chart it is clear the relationship is complex. The question is whether it is too complex; is this is purely noise, or is there some persistence to the relationships captured by the VAR model? This we must answer with backtesting.

Picking the model parameters

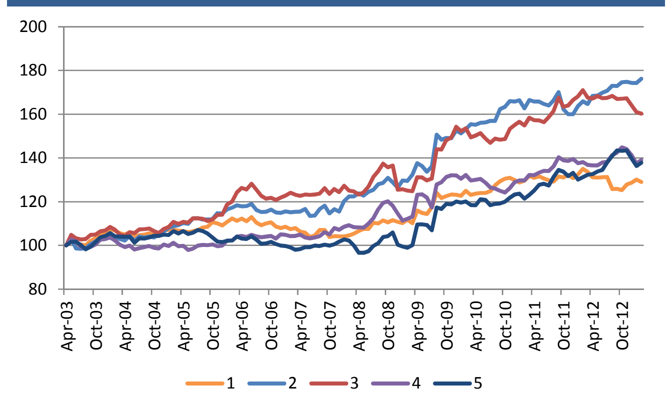
Before we can settle on our final model, we need to decide what parameters to use. Like any quant model, this is part art and part science, and the boundary between optimization and data mining is a narrow one. The first decision is how many stocks we should include in the VAR model for each cluster. As mentioned previously, too many stocks quickly lead to insurmountable dimensionality problems. In Figure 10 we show the Sharpe Ratio for decile spread portfolios based on VAR models with different maximum stock limits. Figure 11 shows the cumulative performance of the portfolios. Note that "max stocks" indicates the maximum number of stocks used in each VAR model, *not including* the source company itself (e.g. the model labeled 2 has a maximum of three stocks in each cluster's VAR model).

Figure 10: Sharpe Ratio of VAR models with different maximum number of stocks



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

Figure 11: Cumulative performance of VAR models with different maximum number of stocks



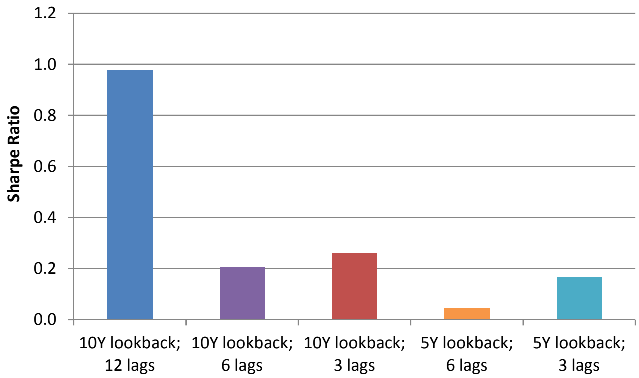
Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

It turns out the sweet spot is two additional stocks plus the source company (i.e. $m = 2$). This yields a Sharpe Ratio of just below 1.0 over the long run, and a fairly consistent wealth curve. At the risk of data mining, we will use a maximum stock limit of two going forward.

Lags and lookbacks

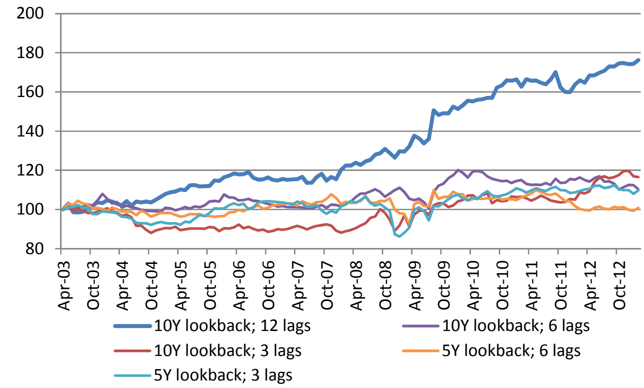
Two other critical parameters are the number of lags to use and the lookback window to estimate the model over. In Figure 12 shows the Sharpe Ratio for models estimated with various combinations of lookback window and lags in the VAR model. Ironically, it turns out our initial base case of a 10 year lookback with 12 lags works out to be the best setting.

Figure 12: Sharpe Ratio of VAR models with different lags and lookback windows



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

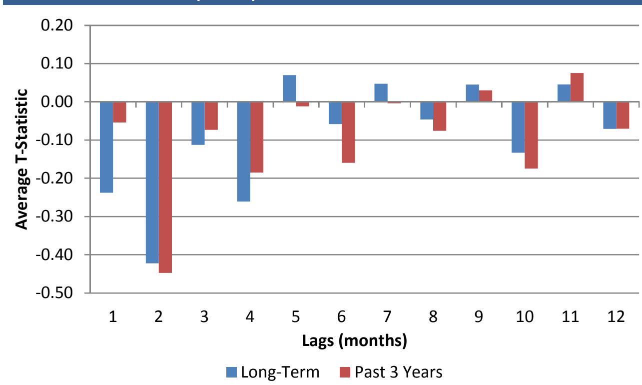
Figure 13: Cumulative performance of VAR models with different lags and lookback windows



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

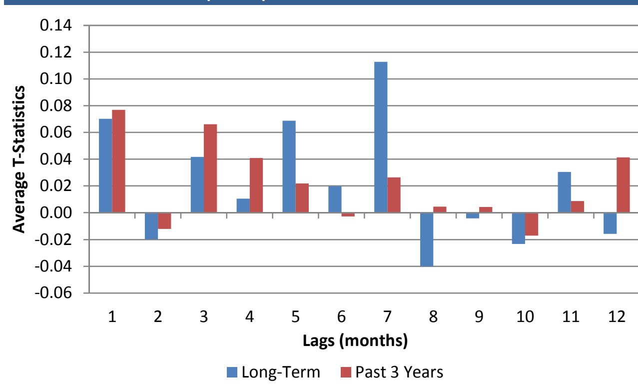
Figure 14 and Figure 15 show the average t-statistics for the coefficients corresponding to each lag of the source company's own returns and the target companies' returns, respectively. Interestingly, on average over time, the model plays more of a reversal effect on about a six month horizon for the source stock itself, and more of a momentum effect for the economically-related companies. The latter result reconciles with the typical finding in the academic literature that momentum of related companies seems to dominate.

Figure 14: Average t-statistics for source company lags (i.e. stock's own past performance)



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

Figure 15: Average t-statistics for target company lags (i.e. other stocks' past performance)



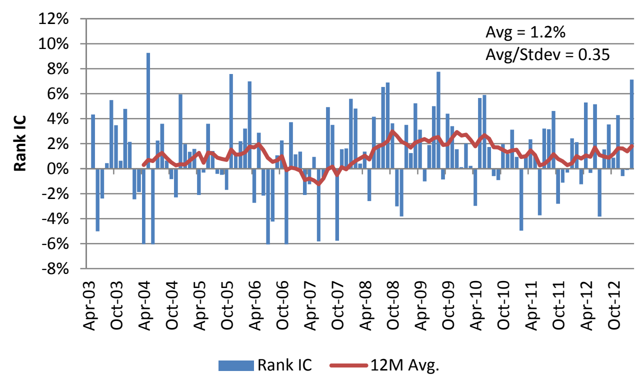
Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Another way to interpret these results is that on average it will want to buy stocks that have been underperforming on roughly a six month horizon, but whose related companies have been outperforming on the same horizon. Buying underperformers whose close peers are rallying would seem to be a somewhat intuitive strategy, even if we arrived at that conclusion in a rather roundabout way. On the other side of the coin, the model would, on average, tell us to sell a stock that has been rallying while its peers have been underperforming, a result that is also somewhat intuitive.

Model performance

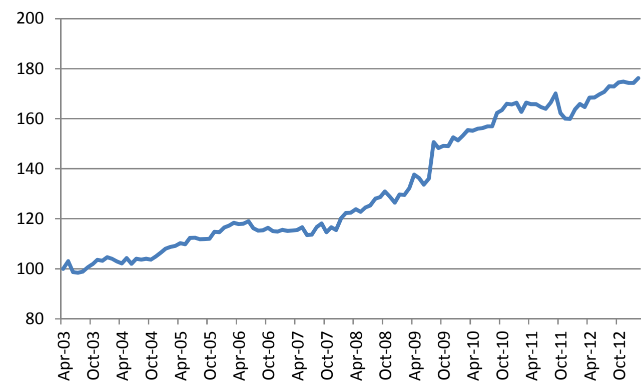
Figure 16 shows the monthly rank information coefficient (IC) for the QLINK model, using the parameter settings described previously (10 year lookback, at most two stocks in addition to the source company, 12 lags). The average IC is 1.2%, which is solid for this universe and time. However the stability of the IC is impressive, with a risk-adjusted IC of 0.35. The consistency of performance is also on display in Figure 17, which shows the cumulative performance of a portfolio that goes long top decile stocks and short bottom decile stocks.

Figure 16: Rank information coefficient for QLINK model



Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank. NOTE: Past performance is not necessarily indicative of future gains/losses.

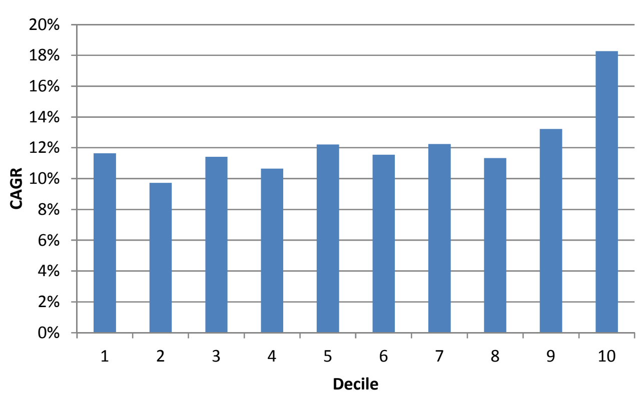
Figure 17: Cumulative top-bottom decile performance for QLINK model



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

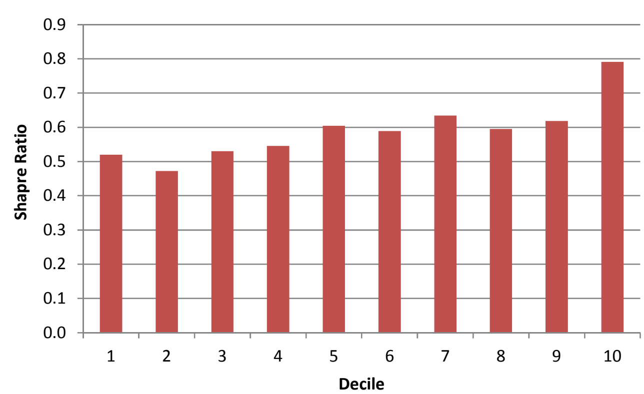
Interestingly, the QLINK model appears to be most effective on the long side. Figure 18 shows the annualized returns of each decile portfolio, and Figure 19 shows Sharpe Ratios for the same portfolios. Decile 10 stocks outperform decile 1 stocks by around 6% p.a., and this difference cannot be explained by increased risk in these stocks.

Figure 18: Average annualized returns for decile portfolios



Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank. NOTE: Past performance is not necessarily indicative of future gains/losses.

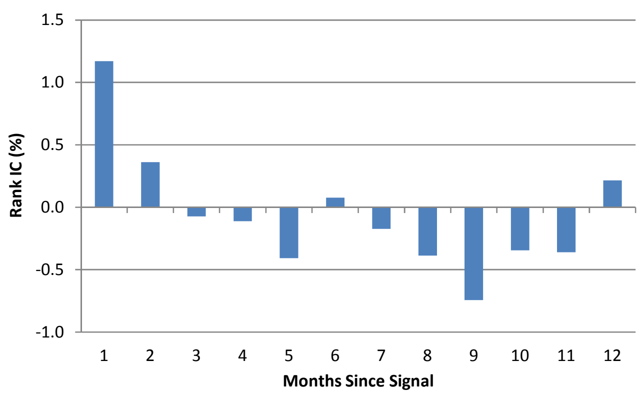
Figure 19: Annualized Sharpe Ratio for decile portfolios



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

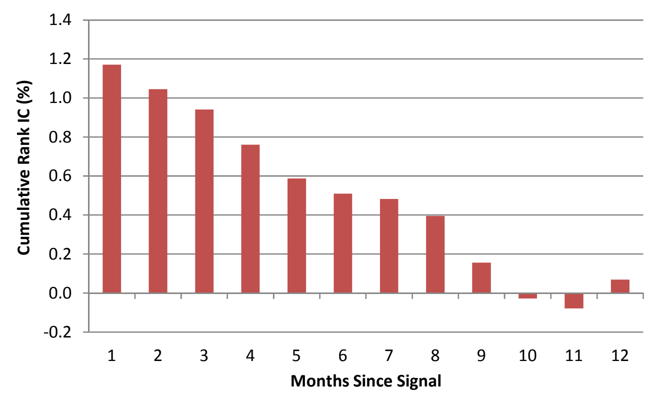
One of the downsides with any time-series return prediction model is that turnover will be high. Returns are extremely noisy, so trying to model them on a stock-by-stock basis at a monthly frequency leads to a stock ranking that can change quite rapidly each month. Figure 20 shows the monthly rank IC decay for the model and Figure 21 shows the cumulative IC decay. The decay is quick; after two months the signal has dissipated. Therefore, transaction costs are going to a critical determinant of the real-world efficacy of the signal. We will address that question in a moment.

Figure 20: Monthly IC decay



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

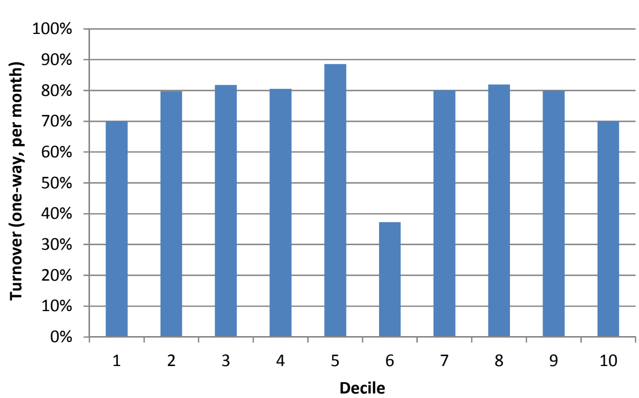
Figure 21: Cumulative IC decay



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

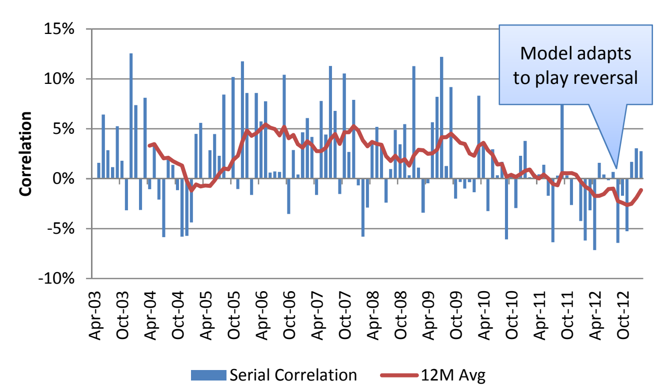
The actual turnover of each decile basket is shown in Figure 22. This chart shows one-way turnover, so remember transaction costs will be 2x the number shown in the chart for a round-trip rebalance (i.e. to sell old stocks and replace with new stocks each month). The extreme deciles have a one-way monthly turnover of around 70%, which is clearly quite high. One reason for this is shown in Figure 23. The cross-sectional correlation of the signal from month-to-month has been declining in the past few years. This is not entirely surprising. In the choppy, risk-on/risk-off market that persisted from the financial crisis until the recent rally, reversal was a strong factor, so it is not surprising that our model has slowly started to adapt to take on a more aggressive reversal stance.

Figure 22: One-way turnover per month, by decile



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

Figure 23: Serial correlation of signal

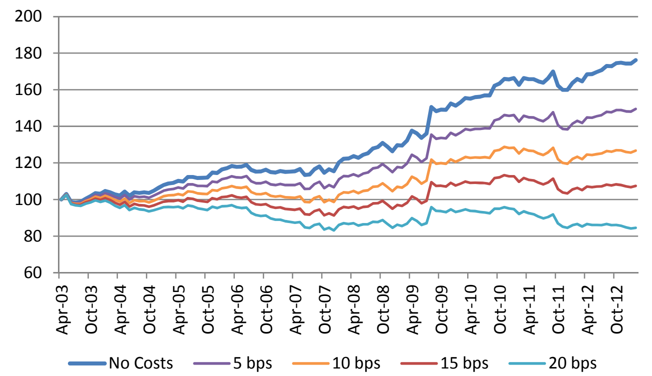


Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

So what about transaction costs?

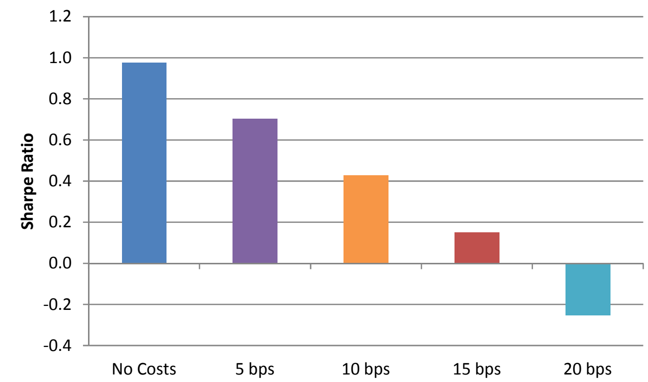
The high turnover raises questions about whether the predictive power of the model will survive transaction costs. We address this in two ways. First, in Figure 24 and Figure 25, we show the performance of a simple long-short decile spread portfolio, under various linear transaction cost assumptions. For a rebalance, we charge these costs twice; for example if the costs are 20 bps then we charge this once for the stocks we sell and again for the new stocks we buy.

Figure 24: Cumulative performance under various linear cost assumptions



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

Figure 25: Sharpe Ratio under various linear cost assumptions



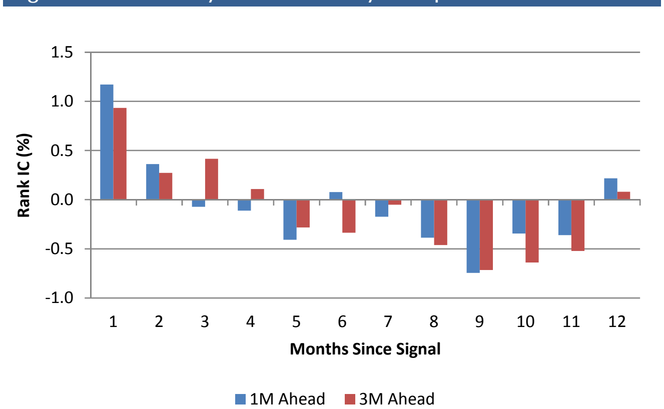
Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

As the charts show, reasonable Sharpe ratios can be achieved at around 5-10 bps one-way costs. However, instead of just letting costs eat away at the model, we can actually try to tailor the model better to the desired holding period. A nice feature of the VAR model is that it can be used to predict not just one period-ahead returns, $r_{i,t+1}$, but also returns further out in the future, $r_{i,t+2}$, $r_{i,t+3}$, $r_{i,t+4}$, …, $r_{i,t+n}$. Of course, as we look further out, the accuracy of the model will fall off, but we might also gain from less turnover. To test this we try a simple experiment: instead of using $r_{i,t+1}$ as our alpha signal, we use $(1+r_{i,t+1})(1+r_{i,t+2})(1+r_{i,t+3})-1$, i.e. the cumulative three month forward return predicted by the VAR models.

Figure 26 shows the monthly rank IC decay of the new signal compared to the base case, and Figure 27 shows the cumulative rank IC decay. This simple change reduces the speed of the decay from about two months to four months (Figure 26) and as a result, the cumulative IC decay maxes out at a three month horizon (Figure 27). Therefore, by simply using the model to forecast a return more in-line with an investor's desired holding period, we can manage the turnover of the model (in this case it falls from about 70% one-way per month to 50% one-way per month).

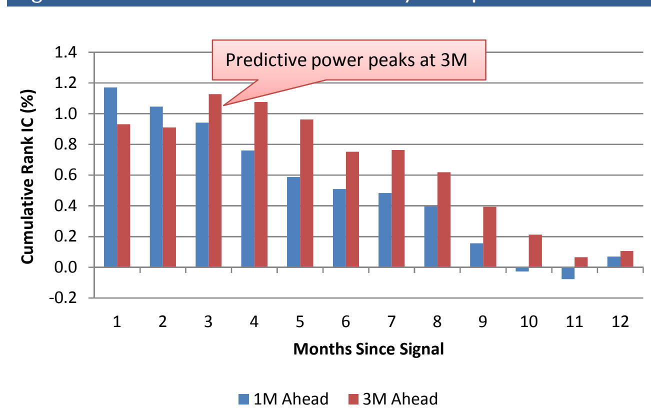
Since everyone faces different trading cost regimes, this flexibility is a useful feature of the QLINK methodology.

Figure 26: Monthly rank IC decay comparison



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

Figure 27: Cumulative rank IC decay comparison



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

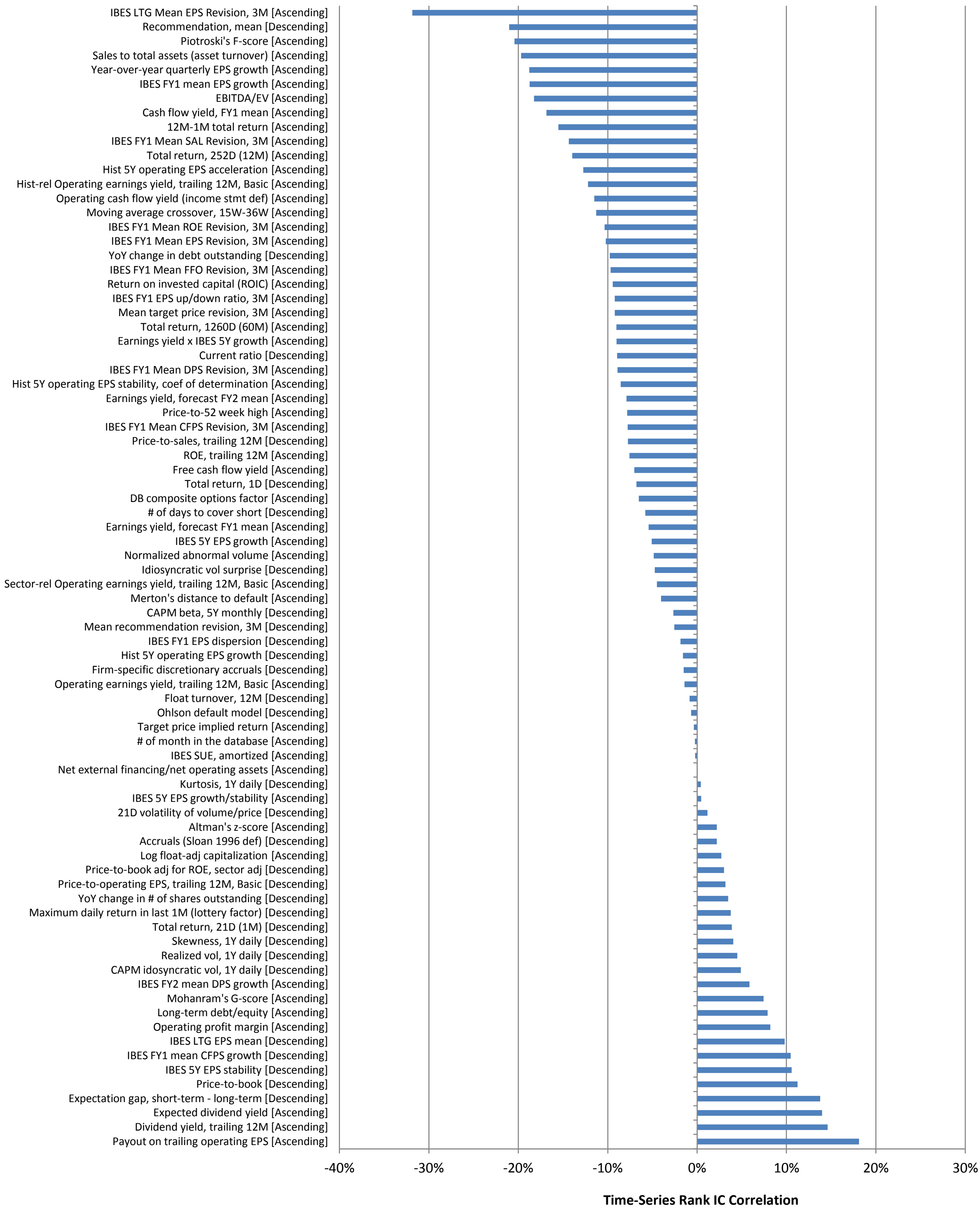
Correlations with common factors

Stand-alone performance for a model is important of course, but the correlation of that performance with other common factors is arguably even more critical. If we could replicate the model with a combination of common factors, then there will be little value-add on top of a more traditional quant model.

Figure 28 shows the time-series correlation of rank IC for the QLINK model and around 80 common quant signals that we track. Note we trade each factor in the direction that yields positive average IC over the long run. For example, if a factor is denoted “Ascending” this means we buy stocks with a high factor score and sell stocks with a low factor score. A factor denoted “Descending” means we buy stocks with low factor scores and sell stocks with high factor scores. The point is that we want to measure the correlation of our QLINK model with the performance of each factor *in the direction we usually trade it*.

The interesting result is that the QLINK model is actually negatively correlated with around two thirds of the factors. This suggests it is quite different from the common cross-sectional quant factors, which is not that surprising given our model is designed in a time-series framework. We also note that the largest positive correlation is less than 20%, so the model is quite unlike any other factor in our library.

Figure 28: Time-series rank IC correlation of QLINK model with other factors



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

Digging deeper

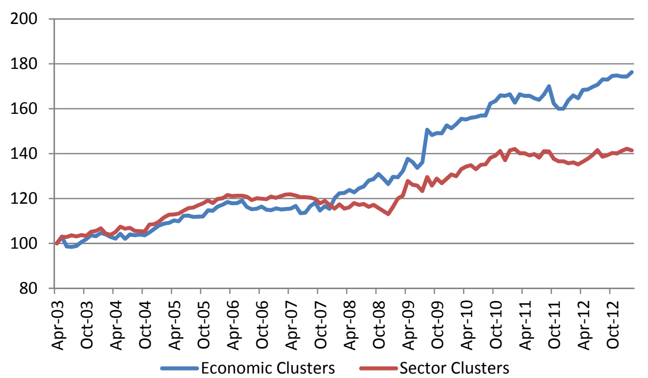
Sectors? Or economic clusters?

So far we have shown that there exists some predictability in the returns of a stock and its economically-related peers. To define such an economically-linked cluster of stocks, we used the Revere database to find companies with different types of economic relationships (e.g. customers, suppliers, competitors, etc.). But could we save a lot of effort and just use sector-based clusters instead? After all, sectors are the most common way to delineate stocks, and presumably stocks in the same sector are at least somewhat economically-linked, because they likely have similar customers and suppliers, and face the same industry headwinds or tailwinds.

To test this, we construct another version of our QLINK model, where instead of using economic-clusters defined by Revere, we use GICS Level 2 Industry Groups. To make a fair comparison, we select the same set of stocks at each point in time that we used in the previous model, except now we use that stock's Industry Group to define its cluster instead of its Revere relationships.

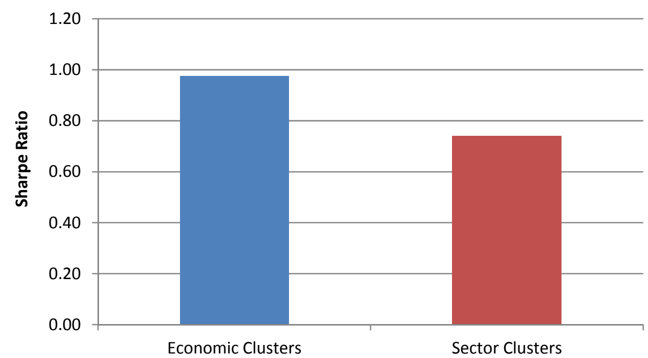
Figure 29 shows the cumulative performance of the two models, and Figure 30 shows the Sharpe Ratios over the backtest period. The results are quite clear-cut; the economic sector model outperforms the sector-based model by a substantial margin.

Figure 29: Cumulative performance for models using economic clusters and GICS Level 2 clusters



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

Figure 30: Sharpe Ratio for models using economic clusters and GICS Level 2 clusters

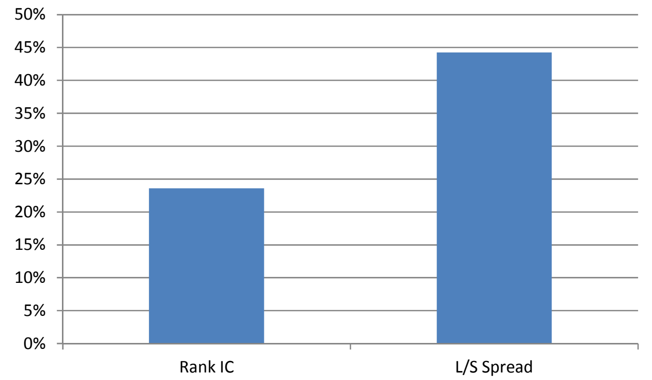


Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

It is also interesting to note that the performance correlation between the sector-based model and the economic clusters model is low, regardless of whether performance is measured using rank IC or decile spread return (see Figure 31). This suggests that a model that combines the two approaches might deliver even better performance than either model individually. For now we will leave this for future research.

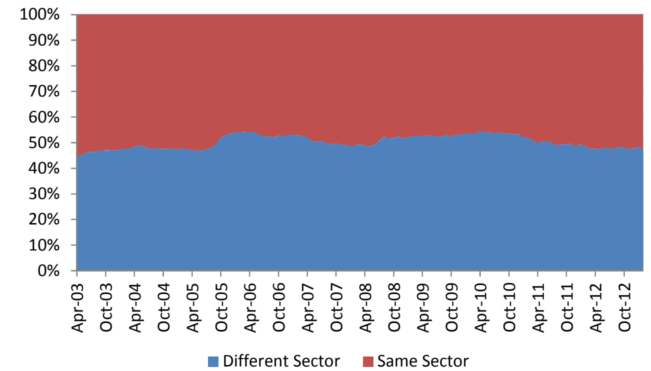
Another way to visualize the difference between the two approaches is to consider the percent of time that the VAR models in the base case model select stocks from the same sector as the source company. The results are shown in Figure 32. It turns out stocks from the same sector as the source company are selected only half the time on average. So the composition of the two models, in terms of companies selected, is very different depending on how we define the cluster. This illustrates again the importance of taking a more holistic view of economic relationships that go beyond sector lines.

Figure 31: Performance correlation between models using economic clusters and GICS Level 2 clusters



Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank. NOTE: Past performance is not necessarily indicative of future gains/losses.

Figure 32: Percent of time economic cluster model selects stocks from the same GICS Level 2 sector as the source company

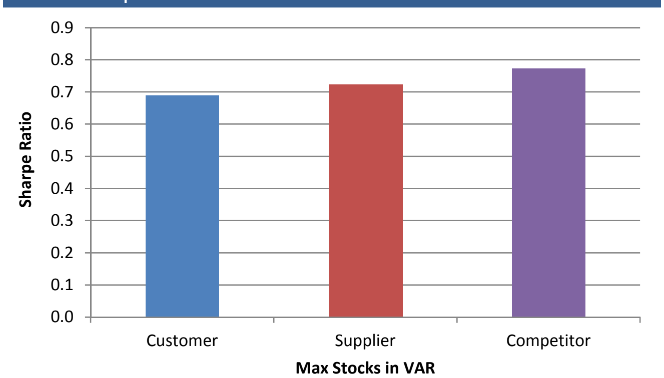


Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Does the type of relationship matter?

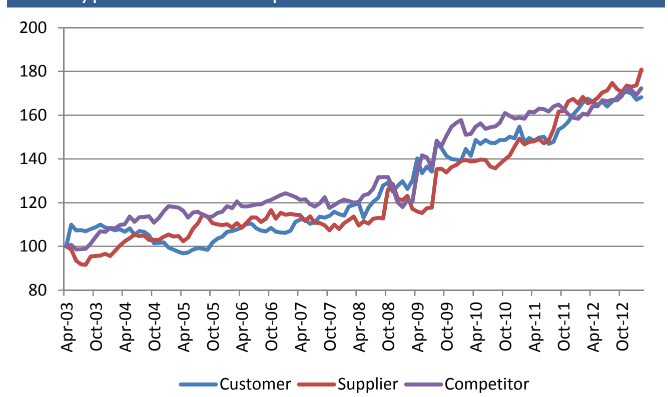
Another interesting question is whether the type of economic relationship matters. As shown in the introduction, Revere captures a wide range of pre-defined relationship types. The three most common are Customer, Supplier, and Competitor. In our base case QLINK model, described in the previous sector, we used all relationship types. But some relationships may be more useful than others. To study this, we run versions of the model that define economic clusters based on each of the three common relationship types. The performance of those models is shown in Figure 33 and Figure 34.

Figure 33: Sharpe Ratio of models built using each type of relationship



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

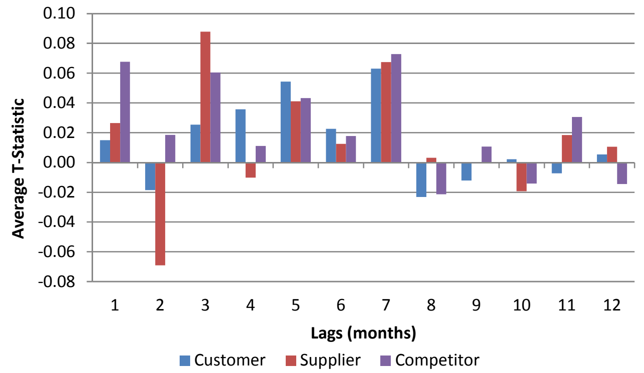
Figure 34: Cumulative performance of models built using each type of relationship



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

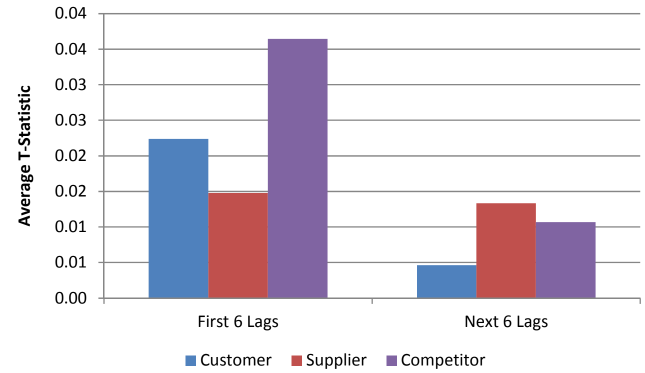
Interestingly, in terms of performance the models actually perform relatively in-line. However, if we examine the structure of the models, we do see some differences. Figure 35 show the average t-statistics for the coefficients for target company returns in each model (i.e. the companies that are not the source company). Figure 36 shows the same, except averaged across lags 1-6 and 7-12, to make things a bit easier to see.

Figure 35: Average t-statistics for target company lags (i.e. other stocks' past performance)



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

Figure 36: Average t-statistics for target company lags grouped by first 6 lags and next six lags



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

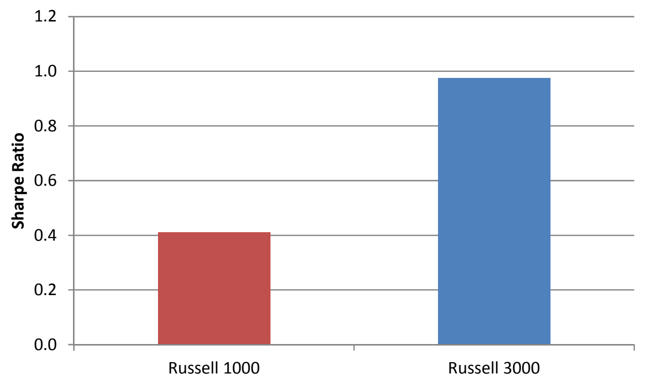
Here we do see some differences. In the near term (i.e. past six months) competitor momentum is strong (see the first set of bars in Figure 36. In other words, if a stock's competitors have been doing well, then that would lead to a higher expected return for the source company. This suggests that, on average at least, if a firm's competitors are thriving, it too is more likely to be doing well; perhaps because the industry is booming. On the flip side, if a firm's competitors are struggling, it appears the impact is more contagion rather than an opportunity for the firm to take advantage of its competitors' shortcomings.

Overall though, there are not enough differences between the models to suggest that separating out the different relationship types is worthwhile, given the somewhat similar performance across the main relationship types.

Large cap results

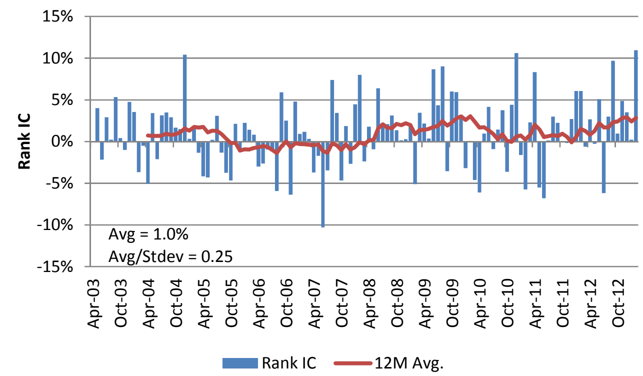
It is also important to check that our results hold in a large cap universe. We do this by re-running the QLINK model in the Russell 1000 universe. As is almost always the case, the performance of the model is weaker in the large cap universe; large cap stocks are typically more heavily scrutinized and arguably more efficiently priced. Nonetheless, the model still delivers a positive Sharpe Ratio and also an IC of around 1% on average (see Figure 37 and Figure 38).

Figure 37: Sharpe Ratio of large cap (Russell 1000) and all cap (Russell 3000) models



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

Figure 38: Rank IC performance for large cap (Russell 1000) model



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

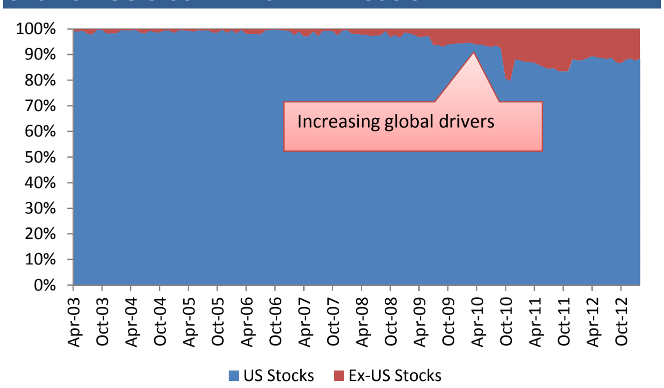
It's a global world

Adding geographic exposures to the model

In our recent research paper "Independence Day" (Luo et al. [2013]), we found that global macroeconomic news is playing an increasingly dominant role in driving US market performance. Does the same apply at the stock level? One interesting way to answer this question is to look at the percent of time that the QLINK model selects non-US companies in its VAR models. Recall that when we indentify the stocks in an economic cluster, we do not restrict ourselves to US names. Therefore, the VAR model for that cluster can potentially pick from a number of US and non-US names, and we impose no constraints on which it should pick (the only criteria for selecting the stocks is the statistical R-squared filter we discussed previously).

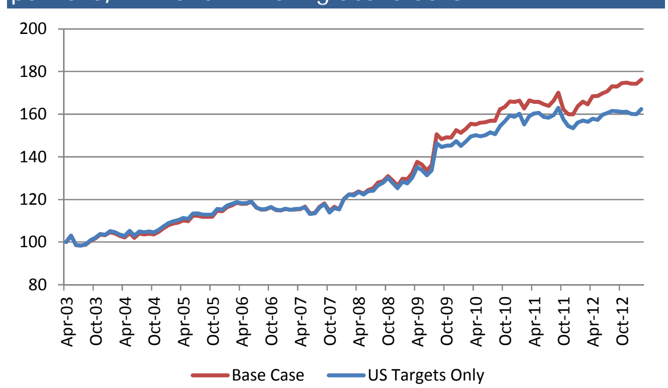
In Figure 39 we show the percent of time that the VAR models at a given point in time select at least one non-US stock. In the early sample the proportion of non-US names was minimal, but now this has increased to over 10%. Note that this result is partly by construction; in recent years Revere has been adding significantly to their non-US coverage, so now there are simply more offshore companies within each cluster. Having said that, Figure 40 is worth noting; this shows the difference in performance between the base case model (which can select from global stocks) and the same model limited only to US stocks. In the period where the global coverage has increased, the performance also improves when adding global stocks into the mix. Therefore, going forward we believe it is extremely important to consider a global universe when searching for related companies (one only has to think of the ongoing battle between Apple and Samsung to see why this is important).

Figure 39: Percent of time QLINK model selects at least one non-US stock in the VAR models



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

Figure 40: Cumulative performance for top-bottom decile portfolio, with and without global stocks



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

Geographic momentum

In addition to considering global stocks when building the model, we can inject geographic data into our model in another way. A useful feature of the Revere database is that it also captures geographic revenue exposure for companies, and maps this exposure to a consistent taxonomy of regions.[2]

The QLINK model is well placed to take advantage of this type of data. Recall that we define an economic cluster as a group of stocks that is linked to a source company though company-level economic relationships. By using the geographic revenue data, we can do the same thing for countries. We do this in a few steps:

1. For a given company, take the reported geographic revenue data at that point in time, and explode into underlying countries. For example, if the company reports that 60% of revenue comes from North America, then we would explode that region into the US, Canada, and Mexico using Revere's taxonomy. If the region accounts for less than 50% of a company's revenue, then ignore that region.

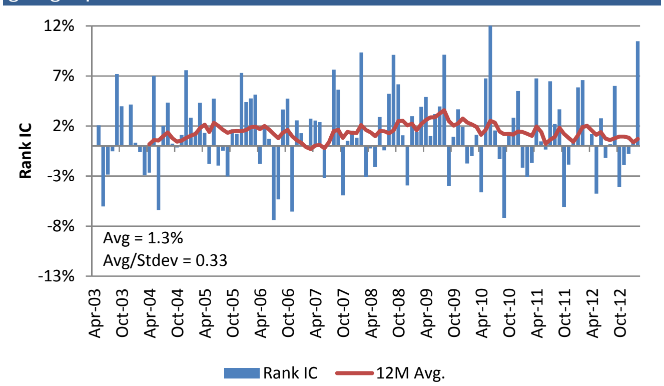
2. Once we have the countries the company is exposed to, we construct equally-weighted market indexes for each of those countries (in this case the US, Canada, and Mexico).

3. We then include these country indexes as additional assets in the economic cluster. For example, if the economic cluster has 10 stocks in it, then we would add the three country indexes into the mix as three additional assets.

4. Now when we run the statistical pre-processing for this cluster, the VAR model can potentially pick the country indexes, the stocks, or both. To keep one information source from dominating the model, we only allow at most one country index to appear in a VAR model, and we keep the maximum number of non-source assets at $m = 2$ (i.e. at most three assets in the VAR model; either the source company plus two target stocks, or the source company plus one target stock and one country index).

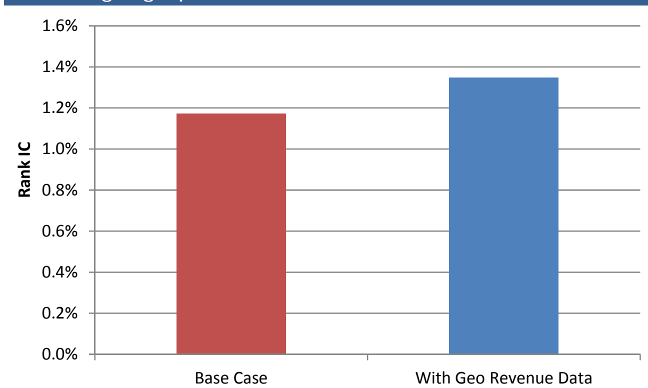
Figure 41 shows the rank IC performance of the model that includes the geographic revenue data, and Figure 42 compares the average IC to the base case model.

Figure 41: Rank IC for VAR model that includes geographic revenue data



Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank, NOTE: Past performance is not necessarily indicative of future gains/losses.

Figure 42: Comparison of average rank IC model with and without geographic revenue data

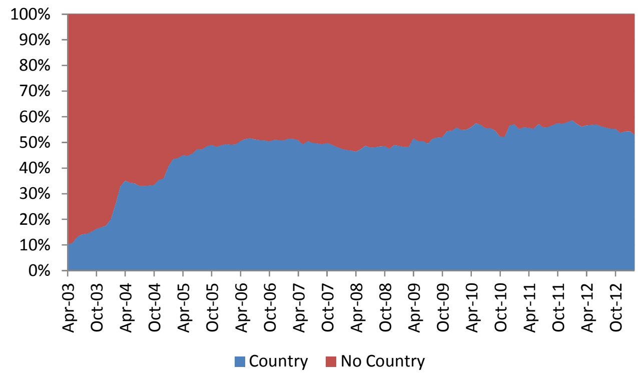


Source: Revere, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

[2] The biggest problem with company reported geographic segment data is that no two companies use the same taxonomy. For example, one company might report US/Europe/Asia while another might use North America/UK/Eastern Europe/Australasia, and so on.

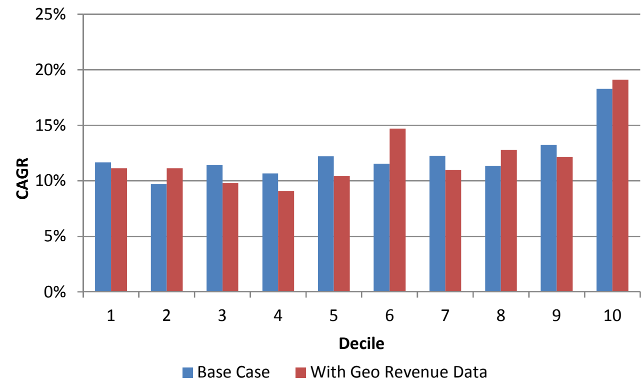
It turns out the addition of the geographic segment data increases the pure predictive power of the signal (measured by average rank IC) by about 15%. Furthermore, when the model has the choice to include country indexes, it tends to do so in about half the VAR models at a given point in time (Figure 43). This is confirmation that from a statistical perspective the past performance of economically-linked countries is at least as important as the past performance of economically-linked companies in explaining the future performance of a given firm.

Figure 43: Percent of time at least one revenue-linked country is selected in VAR model



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

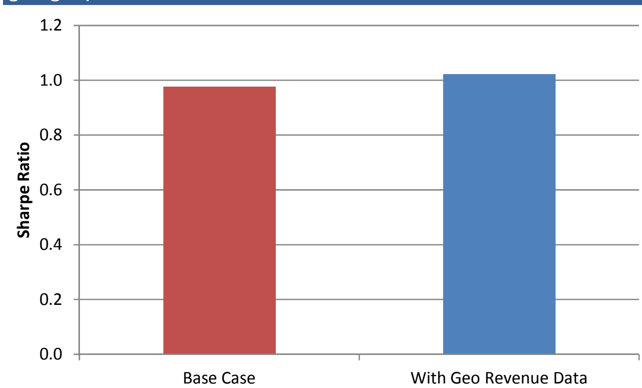
Figure 44: Annualized performance of decile portfolios with and without geographic revenue data



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

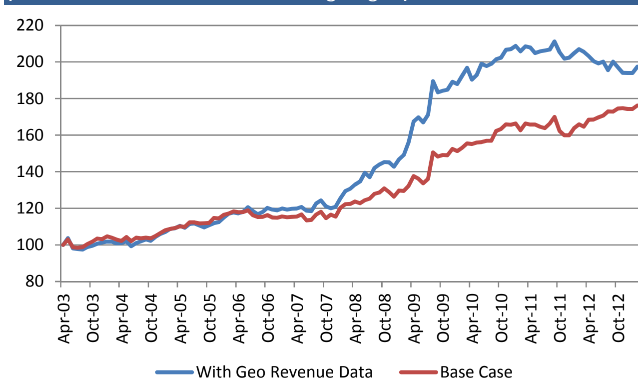
Figure 45 shows the Sharpe Ratios of the two models, based on the performance of a top-bottom decile portfolio, and Figure 46 shows the cumulative performance. The noteworthy result is that up until about the past 12 months, the model that includes geographic data was doing considerably better. However, recent performance of that model has been poor, while the base case model has continued to do well.

Figure 45: Sharpe Ratio for models with and without geographic revenue data



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

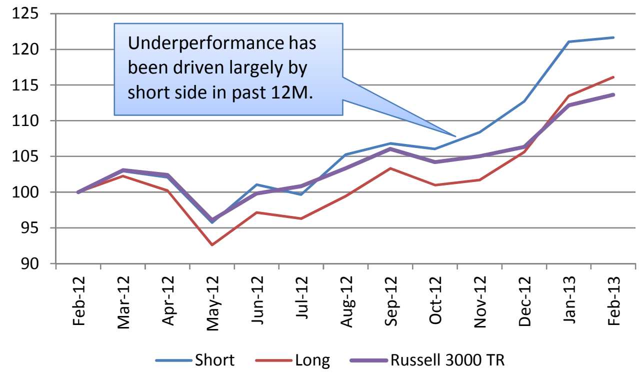
Figure 46: Cumulative performance for top-bottom decile portfolios, with and without geographic revenue data



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

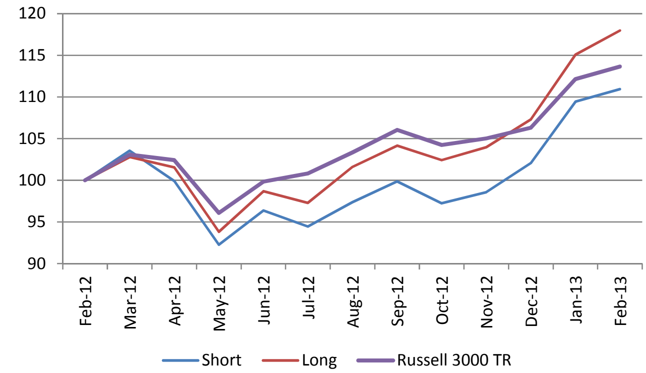
Drilling down into this result, it turns out that the weaker performance of the model with geographic data is largely due to a rally in the short side of the model. Figure 47 shows the cumulative performance of the long and short legs of the model, compared to the market. The short side has been doing well (which is a bad thing for a short position) in the past 12 months, having outperformed both the market and the long side. In contrast, the base case model has continued to perform as we would like, with the long side beating the short side (Figure 48).

Figure 47: Cumulative performance of model with geographic revenue data, past 12 months



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

Figure 48: Cumulative performance of model without geographic revenue data, past 12 months



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

We will continue to track the performance of both models, to help us understand whether the weakness in the model with geographic data is temporary or reflects a secular change in the market. We also plan to do further research to better understand what is driving this underperformance.

Conclusion

Ideas for future research

In this paper we have illustrated some of the benefits that can often accrue from using granular company-level relationship data. The QLINK model we proposed is a hybrid model that uses both underlying economic relationships and past statistical relationships to try to predict future returns. We hope our analysis will provide ample ideas for future research, and indeed we have some plans to do some further research of our own. Some of the interesting questions that we hope to study are:

- **Tighten the pre-processing step to make better use of the detail provided in the Revere database.** For example, Revere uses a proprietary algorithm to estimate a company's revenue exposure to different countries, even when the company doesn't directly report that revenue.[3] Using this more granular data could help us eliminate countries that do not matter, without the risk of spurious regressions that is inherent in the statistical pre-processing step. The same goes for the company relationships; Revere also offers a product called Relationship Analytics where it uses an algorithm to interpolate missing data in a matrix of customers and suppliers. Using this information could also allow pre-processing based on estimated economic links, which might be more accurate than a purely statistical approach.[4]
- **Include business segment information in the model.** Revere also maps a company's revenue to a consistent taxonomy of business lines. Using this, we could construct stock price indexes for different business lines (by aggregating the performance of all companies that derive revenue from smartphones for example). We could include these indexes as additional potential variables for the VAR models to select from, in the same way that we added in country indexes.
- **Apply the same ideas to company fundamentals instead of stock price returns**. One of the weaknesses of the QLINK model is high turnover. One way to slow this down might be to fit the model to company fundamentals instead of returns. For example, the time-series of a company's EPS is much less noisy than its return series. Perhaps this would give us a better model to use for longer-term investors, who cannot trade a high turnover model like the QLINK model.

[3] For example, Revere uses things like the GDP share of each country in a region to allocate a company's revenue to the individual countries in that region. We have not used that estimated data in our model; currently we only use revenue numbers where the company actually reported them.
[4] See McGill and Mingardi [2010] for more details.

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Appendix 1

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