Hedging Risk Factors

Bernard Herskovic, Alan Moreira, and Tyler Muir*

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Abstract

Standard risk factors can be hedged with minimal reduction in average return. This is true for "macro" factors such as industrial production, unemployment, and credit spreads, as well as for "reduced form" asset pricing factors such as value, momentum, or profitability. Low beta versions of the factors perform close to as well as high beta versions, hence a long short portfolio can hedge factor exposure with little reduction in expected return. For the reduced form factors this mismatch between factor exposure and expected return generates large alphas. For the macroeconomic factors, hedging the factors also hedges business cycle risk by significantly lowering exposure to consumption, GDP, and NBER recessions. We study implications both for optimal portfolio formation and for understanding the economic mechanisms for generating equity risk premiums.

*UCLA, Rochester, UCLA & NBER. We thank Valentin Haddad, Lars Lochstoer, and Ivo Welch for comments.

This paper shows that standard risk factors can be hedged at low or no cost. We first show this for macroeconomic factors such as industrial production, unemployment, and default risk indicators, all of which are strongly correlated to the business cycle. By hedging these factors, we show that we also hedge the market exposure to consumption and GDP at monthly to yearly frequencies, and produce portfolios that – on average – do *well* rather than poorly in recessions. We combine these factors with the aggregate stock market and show that we reduce business cycle risk without impacting average returns. Next, we hedge "reduced form" asset pricing factors such as value, momentum, and profitability – and again show that such hedges have surprisingly low cost. Because of this, the low beta versions of the reduced form factors have strong positive alphas on the factors themselves – they have relatively similar average returns but low factor betas. The main fact in this paper is that all of these factors (both reduced form and macro) can be hedged out of a portfolio with a minimal reduction in expected returns. This has important implications both for optimal portfolio formation and for understand the economic origins of risk premiums.

To fix ideas, we start with the standard asset pricing equation:

$$E_t[R_{i,t+1}] = -cov_t(m_{t+1}, R_{i,t+1})$$

where m is the pricing kernel or stochastic discount factor (SDF) that prices all assets. One can write this in familiar "beta" representation as well. An asset pricing model means specifying a candidate for m. The asset pricing literature considers both reduced form and economically motivated representations of the SDF. The reduced form factors include pricing models such as Fama and French (1996) who specify $m = -b'[Mkt, SMB, HML]$ for some weights b, though this can be easily extended to other reduced form factors as well (i.e., momentum). The macro-finance literature typically specifies the SDF in terms of macroeconomic variables that proxy for marginal utility, i.e., consumption, GDP, industrial production, or employment. From an economic perspective, these variables capture the idea that stocks are risky because they do poorly in bad times when marginal utility is high.

A typical approach to testing this equation is to use "test assets" that exploit dispersion in expected returns (the left hand side) and then checking if this dispersion is matched by covariance with a set of factors. Test assets may include portfolios formed on book to market ratios, past returns, and so on.[1] Instead, we create portfolios that create dispersion in the right hand side, i.e. dispersion in factor exposures, following the portfolio formation techniques in Fama and French (1992).

Specifically, for each factor we form portfolios by sorting stocks into deciles based on their factor beta over a trailing window (5 years of monthly data for our macro factors; 3 years of daily data for traded return factors). We then value-weight the stocks within each beta-sorted portfolio decile.[2] We find that the pre-formation betas used to sort stocks into portfolios are strong predictors of portfolio post-formation beta. In other words: the factors can all be hedged in that a real time long-short portfolio can be created that has reliably negative ex-post beta on the factor. Importantly, this strong pattern of predictability of post-formation betas is true for both traded and non-traded risk factors. We then form these hedge portfolios by constructing low minus high beta versions of each factor and find that this resulting portfolio has a strong negative beta on the factor itself. Thus, one can create an effective hedge for the factor where "effective" is judged both statistically and economically.

Surprisingly, the expected return on the hedge is *not* strongly negative, despite having a significantly negative exposure to the factor (e.g., it works as factor insurance). Indeed, in most cases the average return of the hedge is statistically and economically close to zero. The reason for this is a relatively "flat" slope of the beta vs expected return of the factors – roughly speaking the low and high beta portfolios have average returns that are too similar given the spread in betas. The implication is that one can add the factor hedge to a portfolio and lower the factor betas without decreasing the portfolio average return. The fact that our portfolios are all value-weighted means that this flatness has important economic implications as the failure of the model is driven by variation in factor betas of large stocks which are easy to trade and any "mispricing" is relevant for the broader

[1] See Lewellen, Nagel, and Shanken (2010) for issues evaluating factor models with these test assets, and Bryzgalova (2017) for issues with having little variation in factor covariances when evaluating models.

[2] The use of post-formation betas, rather than regressions of returns on lagged betas, as well as our use of value-weighted returns distinguishes our procedure from other work such as Chen, Roll, and Ross (1986) who use a standard Fama and MacBeth (1973) procedure.

economy.

We then combine the macroeconomic hedges with the market return – the idea is to start with the market return as a default portfolio and then see how adding the hedge changes the portfolio risk-return profile. We focus on industrial production, unemployment, credit spreads, and the slope of the term structure as macroeconomic factors because of their strong connection to the business cycle, their higher frequency time-series (they are available monthly which we show is important to construct effective hedges using our rolling approach), and because they have been shown to drive variation in returns (Chen et al., 1986). First, the market portfolio alone is significantly exposed to these business cycle factors such as industrial production, unemployment, credit spreads, the slope of the term structure and other recession indicators including NBER recession dummies. Next, adding the hedge portfolio reduces or eliminates these exposures but keeps the same average return. Further, we show that hedge portfolios help reduce or eliminate market exposure to GDP or consumption. We do not create hedges for consumption and GDP directly due to their availability at lower frequency (i.e., they are quarterly instead of monthly), but we show that by hedging the monthly macroeconomic series we also implicitly hedge consumption and GDP exposures. The implication is that one could achieve roughly the same expected return and Sharpe ratio as the market without significant exposure to the business cycle. This means the explanation for the equity premium can not rely on exposure to these factors alone. We also show that our hedges work to hedge consumption factors that previous work argues are priced in the cross-section of returns, including the factors of Parker and Julliard (2005), Jagannathan and Wang (2007), and Kroencke (2017). Thus, our construction of independent test assets formed on macro risk exposures appears important for evaluating existing macrofinance based pricing factors.

We show the implications of this result as well for the traded reduced form factors (i.e., Fama and French (1996), Fama and French (2015)). Here the economic interpretation extends if one views these reduced form factors as proxies for risks investors care about. We show that hedging these factors also has surprisingly low cost. This means that the price of risk estimated from the beta sorted portfolios on these factors appears "too low".

Because these are traded factors, this translates directly into alphas – the low beta portfolios always have high alpha on the factors themselves, and the high beta portfolios have negative alpha. While these facts are well known for the market portfolio (e.g., Black (1972), Jensen, Black, and Scholes (1972), Frazzini and Pedersen (2014)), we show that it is in fact pervasive across factors.[3] In contrast with Frazzini and Pedersen (2014) who focus on equal-weighted portfolios, we focus in value-weighted portfolios in most of this paper. Therefore, the empirical patterns we document have implications that are relevant to a large share of the stock market in terms of market values.

For the traded return factors, we can push our analysis one step further and combine factors into a single portfolio by forming the ex-post mean-variance efficient combination of the factors (that is, the combination of traded factors that produces the highest full sample Sharpe ratio). By definition, this MVE portfolio contains all pricing information of the factor model in question. We then show that one can hedge the MVE portfolio – the low minus high beta version of this portfolio has strongly positive alpha on the original MVE portfolio, despite the fact that the MVE portfolio was chosen optimally ex-post to summarize all factor pricing information. A closely related result across factors is found in Daniel et al. (2017) though we show how our construction differs and, importantly, we show that our empirical results are distinct from theirs in that they survive when controlling for their factors.[4]

Next, we derive implications for mean-variance investors. Specifically, we form portfolio weights for the cross-section of stocks by assuming that all stock returns have the same mean, and we use common factors to reduce risk exposure. Thus, we assume that there is no dispersion in expected returns generated by the factors, and only use common time-series variation in the factors to minimize risk. This results in the minimum variance portfolio formed taking the factor loadings into account, i.e. assuming that the stocks variance-covariance have a factor structure.

We show that this minimum variance portfolio results in only a modest decline in average return compared to an equal weight portfolio of all stocks, but it results in a dramatic reduction in risk. If all factors were fully priced, this would not be the case,

[3]See also Daniel and Titman (1997) and Daniel, Mota, Rottke, and Santos (2017).

[4]See also Daniel and Titman (1997), Kelly, Pruitt, and Su (2018), and Levi and Welch (2017).

because any reduction in risk (achieved by essentially avoiding beta loadings) would result in a sacrifice in expected return of the same proportion. Thus, the "flat slopes" of each factor result in a reduction in risk with little sacrifice in return.

Our results relate to a long literature on the cross-section of expected returns. Harvey, Liu, and Zhu (2016) provides an extensive documentation of all the factors proposed to explain variation in average returns, and Fama and French (1992, 1996) are the classic references for the overall methodology applied in this literature which typically proceeds as: (1) find cross-sectional variation in average returns that cannot be explained by standard factors, (2) propose a new factor that captures this variation. Daniel and Titman (1997) and Frazzini and Pedersen (2014) are notable exceptions. Here we follow their approach and look for portfolios with cross-sectional variation in factor betas and show that this variation is not matched with variation in average returns. This failure of factor betas and return being tightly linked is analogous to the time-series results in Moreira and Muir (2017) who show factor volatilities are not associated with factor risk premiums – thus reducing factor exposure in high volatility periods improves mean-variance outcomes. Similarly in our setting we improve mean-variance outcomes by exploiting the weak line between exposure and risk premiums.

We also relate to a long literature studying the pricing of macroeconomic variables Chen et al. (1986). An innovation relative to this work is that we focus on portfolios with strong cross-sectional variation in factor betas. This is important because it gives our empirical tests power to evaluate the different risk-factors. We shed additional light on the literature exploring the market covariance with macro variables (e.g., aggregate consumption) as explanations for equity risk premiums (Breeden (1979), Campbell and Cochrane (1999), Lettau and Ludvigson (2001), Bansal and Yaron (2004), Lettau and Ludvigson (2009), Lewellen et al. (2010), Greenwald, Lettau, and Ludvigson (2014)).

The paper proceeds as follows. Section 1 describes our data. Section 2.1 analyses macro factors. Section 2.2 analyses reduced-form risk factors. Section 3 concludes.

1. Data Description and Methodology

1.1 Data and methodology

We consider all stocks from the CRSP with share codes 10, 11, and 12. The risk-free rate, the market returns as well as all asset pricing factor data come from Kenneth French's website, except for the betting against beta (BAB) factor which comes from the AQR website and the DMRS factors from Kent Daniel. When using daily returns data, asynchronous trading is taken into account by using average return in every three-day trading window. All macroeconomic data are monthly series taken from the Federal Reserve Economic Data (FRED) maintained by the St. Louis Fed. We consider the Moody's BaaAaa spread, industrial production, initial claims (aggregated monthly from weekly data), and the slope of the term structure computed as the 5 year Treasury yield minus the 3 month T-bill. We also use monthly NBER recession indicators and quarterly real per capita GDP and consumption.[5]

Our portfolio approach methodology follows closely that of Fama and French (1992). To construct our portfolios at month t, first we compute betas relative to a factor over some past window. That is, we regress stock i's returns on asset pricing factor f:

$$R_{i,\tau} = a_{i,t} + \beta'_{i,t} f_\tau + \varepsilon_{i,\tau},$$

For traded factors, which are available daily, we run this regression using daily data over the past 36 months. Thus in this case τ represents a day in the 36-month window from month $t-36$ to month $t-1$. We require a minimum of 100 observations to run these daily regressions. For macroeconomic factors, which are available monthly, we run this regression over the past 60 months. In this case τ represents a month in the 60-month window from month $t-61$ to month $t-2$. Notice that we use one extra lag in this case

[5] Stock return data is from 12/1925 to 12/2016. We use industrial production data from 12/1925 to 12/2016, initial claims data from 2/1967 to 12/2016, Moody's BaaAaa spread from 12/1925 to 12/2016, and slope of the term structure from 5/1953 to 12/2016.

to take into account the fact that the monthly macroeconomic series are announced with a one month lag, thus ensuring these portfolios are formed in real time. For some macro factors, we also take into account that stock returns may lead the series somewhat (e.g., bad news about the economy could drive down stocks today but industrial production may decline next month). To account for this, we also consider 3 and 6 month changes in macro variables rather than the 1 month changes. For 3 month changes, we use the stock return in the month $t-5$ with the change in the macro variable from $t-5$ to $t-2$ – which ensures the portfolio could be formed in real time given the 1 month publication lag in the series.

We then assign stocks i in the above regression to deciles based on their factor betas $\beta_{i,t}$. Next, we form a value weighted portfolio of the stocks in each one of the deciles. We use value weights to avoid influence from small or microcap stocks in the procedure.[6] This procedure forms our beta sorted portfolios and we analyze the returns of these portfolios over a future period.

2. Empirical Results

2.1 Macroeconomic factors

Macro hedge portfolios

In Table 1 we show results for portfolios that hedge macroeconomic risks including industrial production, initial claims (unemployment), credit spreads, and the slope of the term structure. These factors are important because they measure economic activity over the business cycle and are also the factors studied by Chen et al. (1986) who argue they are

[6]One remaining concern is if beta and size are correlated then our deciles may correlate strongly with size (e.g., bucket 1 could be made up of mostly small stocks). We find this is not the case. Most concretely, we find that if we compute the absolute value of the alpha for each decile and then value weight across deciles we arrive at similar magnitude of alphas as if we equal-weight across deciles. Thus we stick to only value weighting within decile but equal weighting across deciles for simplicity.

important drivers of stock returns. The hedge factor is always the low minus high beta portfolios of each factor. The methodology section outlines the portfolio formation in more detail, but as an important reminder we change the sign of all factors such that they go down in bad times and up in good times (in other words all factors are essentially pro-cyclical – thus the sign is comparable to the market or any other factor that does poorly in bad times). This means we take the negative change in initial claims to unemployment and negative change in credit spreads. The low minus high is thus always designed to hedge the factor risk by providing insurance against bad times.

In Table 1 Panel A, we begin by documenting the annualized average returns of this hedge factor. The average returns are generally near zero (statistically and economically). In fact, the average across all rows is, if anything, slightly positive meaning the point estimate goes the wrong way – that is you often got paid to hedge in sample. The last rows of Panel A document post formation betas of the hedge factors. If pre-formation betas that we sorted on were extremely noisy, we may not end up with a good factor hedge and a significant post-formation beta. Instead, we find that the hedge factor does actually hedge – there are large statistically significant negative betas on all factors. The fact of looking at post formation betas explicitly also differentiates our approach from running Fama-MacBeth regressions of individual returns on pre-formation betas. In that case, a low price of risk could potentially come from noisy beta estimates where we look at post-formation betas directly. In the Table, the labels 1, 3, and 6 relate to the horizon the change in the macro variable is computed over when correlating with returns as described earlier – in particular we allow that stocks may react in real time to bad economic news that affects industrial production and initial claims over the coming months, thus we consider computing beta of stock returns in a month with the change in these variables over the next several months. This issue is less important for credit spreads which are a market price that also reacts in real time to bad economic news, similar to stocks.

In Table 1 Panel B, we then combine the hedge portfolio with the value weighted market portfolio. The idea is to see how adding the hedge portfolio to the market changes its risk-return characteristics. That is, one could think of starting with the market as their portfolio and then exploring how adding the hedge changes your portfolios' risk-return profile. In the first row, we show that average returns are not much changed, which simply follows from the fact that the average return of the market plus hedge portfolio is the average return of the market plus the average return of the hedge portfolio (which are all near zero). Next, we see that adding the hedge portfolio doesn't have a large impact on Sharpe ratios – sometimes Sharpe ratios increase, other times they decrease but on average Sharpe ratios are about the same as holding just the market. In the last row we show that the market – on its own – is naturally exposed to all of the factors in a positive way. That is, if one were to only hold the market portfolio, one would be exposed to industrial production shocks (the "market exposure" is defined as the beta of the market return regressed on the factor itself). The preceding line, post-formation beta, shows that once the hedge portfolio is added to the market, factor exposures drop to nearly 0. That is, the hedge portfolio eliminates the factor risk completely from the market. Thus, the market plus hedge portfolio has on average the same return and Sharpe ratio as the market, but no longer has exposure to the factor risk.

In Table 1 Panel C, we show how these market hedged portfolios load onto other business cycle risks. Specifically, we compute returns during NBER recessions. To do so we regress returns on monthly recession dummies and report the coefficient and t-stat.[7] For the unhedged market (first column), we see that the return is on average 30% lower during recession periods. Moving across the columns, we find that the hedged market does

[7]While not critical for our results, we allow a 1 quarter lead time for the relation between returns and recessions – that is, stocks tend to fall just *before* the official start date of the recession, and we capture this by shifting the recession dummies by 1 quarter. This helps capture the slight difference in timing between returns and the recession dummies, but our results qualitatively hold if we make the relationship contemporaneous as well.

relatively better in recessions than that market – though this is not true for every factor individually. The average drop in recessions across all the market plus hedge portfolios is around 17%, meaning the hedge portfolios go some way towards hedging recession risk – the hedge portfolios do about 13% better on average than the unhedged version of the market during recessions, reducing the recession exposure by over 40%. This occurs because the factors themselves are significantly associated with the business cycle. All factors are strongly correlated with recessions, thus hedging the factors naturally reduces exposure to recessions.

We next show that the hedged portfolios decrease exposure to other business cycles measures – namely GDP and consumption. These variables are only available quarterly, hence it is hard to compute rolling betas to form hedge portfolios on them directly as there are too few observations making the hedges noisy. Instead, we show here that by hedging industrial production we implicitly hedge consumption and GDP – roughly speaking the monthly industrial production is a higher frequency measure of economic activity that strongly correlates with the business cycle, so by hedging IP we also hedge consumption and GDP. To show this, we cumulate our portfolios returns quarterly and regress them on quarterly log changes in real per capita consumption and GDP. The results confirm our intuition: the hedge portfolios reduce consumption and GDP betas by large amounts, almost always to insignificance. We also show a meaningful reduction in exposure when we consider annual measures of GDP and consumption instead of quarterly ones.

Finally, we consider the exposure of our hedge factors to consumption asset pricing factors argued to pick up variation in risk premiums in the literature. We consider long term consumption, taken as consumption over the following three years as used in Parker and Julliard (2005), fourth quarter consumption as used in Jagannathan and Wang (2007), and unfiltered consumption as used in Kroencke (2017). All these measures are argued to be priced in the size and value portfolios, and our construction of these factors is identical to those in the previous papers.[8] We find that our hedge portfolios generally have negative exposure to these factors as well. In particular, the hedge portfolios lower the exposure of the market portfolio to long run consumption and unfiltered consumption. The decline for fourth quarter consumption is less pronounced, while the decline for long term consumption is the strongest. Taken together, our macro hedge portfolios appear to hedge other factors that have been argued to capture the SDF better than the standard aggregate consumption series.

Slopes of factor betas

The previous results suggest that macroeconomic risks are not strongly priced, such that the slope of the line that plots beta vs average return is "too flat." However, because these are non-traded factors, it is hard to know from the current results what the premium should be per unit of exposure.

Here we test whether the slopes are too flat as follows: we run standard two-pass asset pricing tests using the 10 portfolios sorted on betas as test assets and using the macroeconomic variable as the asset pricing factor. More specifically, for each factor we test:

$$E[R_i] = \lambda_0 + \lambda_1 \beta_{i,f},$$

where $\beta_{i,f}$ is the beta of portfolio i on factor f (e.g., the post-formation beta), $E[R_i]$ is the portfolio average return, λ_1 is the price of risk of factor f, and λ_0 is the intercept.

We use λ_0 as a measure of whether the slope is "too flat". In particular, we compare λ_0 to the average return across all portfolio. If λ_0 is small – near zero – then the slope of beta vs average return is very steep. If λ_0 is very large, then the large intercept implies are relatively flatter slope. A perfectly flat slope is one in which λ_0 is equal to the average return across all portfolios.

We run this test using the standard two-pass regression methodology, and we report

[8] See Parker and Julliard (2005), Jagannathan and Wang (2007), and Kroencke (2017), respectively.

the estimated coefficients λ_0 and λ_1 along with Shanken corrected t-statistics (which correct for the fact that betas may be noisy from the first stage regression).

We find that λ_0 is economically very large in all cases. In fact, λ_0 is as large as the average return across all portfolios, meaning that the beta vs expected return lines are completely flat. The prices of risk λ_1 confirm the same thing: they are near zero in every case and never statistically significant. While this is a formal test showing that there is a mismatch between exposure and average return, it should be intuitive given our results in the previous section. More specifically, the value λ_0 is the "zero-beta" portfolio, it tells you the expected return when there is no exposure to the factor. The fact that it is just as large as the average return across all portfolios implies that one can keep the same average return without the factor exposure – one can hedge the factor essentially for free.

Evaluating Existing Priced Factors

We next evaluate the priced consumption factors mentioned earlier, specifically the factors of Parker and Julliard (2005), Jagannathan and Wang (2007), and Kroencke (2017), all of which are based on consumption data. We run the same asset pricing tests as before. The results are in Table 3. To compare to the previous studies, we use the Fama-French 25 size and book-to-market portfolios (FF25) as test assets in the first column, consistent with the original papers. Next we evaluate the same models using our beta sorted portfolios as the test assets. Several results are worth noting. First, we consistently obtain much smaller prices of risk for the factors (λ_1) for our test assets compared to the FF25. Importantly, this is not because our test assets are less informative – we report standard errors below the point estimates and generally find the standard error for the factor price of risk is about the same using the FF25 or any of our 10 beta sorted portfolios. This is important – it could have been that the factors had no spread in exposures to our test assets, hence the price of risk of risk may just be noisy. If that were the case, it would not be obvious our test assets add much economically. Instead, we find about the same order of statistical precision just a lower magnitude of the price of risk. Using our test assets, none of the factors appears significantly priced. In many cases, the price of risk we estimate is more than two standard errors away from that estimated on the FF25, highlighting the conflict across the test assets.

Next, we note that the intercept (λ_0) is typically much larger with our test assets compared to the FF25 – again consistent with a "flat slope" (the higher is the intercept on the beta vs expected return line, the flatter the slope will be). Again, as this number should theoretically be zero, it highlights the struggle of these factors to price the test assets. Finally this same conclusion is reflected in the cross-sectional R^2 which is much lower on average in our test assets compared to the FF25. Overall, the asset pricing exercise highlights our earlier points: macro risks appear to be relatively easy to hedge at "too low" of a cost (in most cases the hedge is nearly free). This point goes beyond just the failure of the CCAPM and shows up in additional macro factors argued to price the cross-section of returns. Judged from this standpoint, their price of risk appears too low when studying the cross-section we form on macro risks.

2.2 Reduced form factors

Univariate factors

We now consider traded "reduced form" factors used in the asset pricing literature. We conduct the same exercise in spirit but with a few empirical changes. First, we now have daily data for these factors, so we use three years of daily data to form beta portfolios. Second, because the factors are traded, we can use standard time-series alpha tests of the low beta portfolios on the factors themselves, which simplifies the analysis. Third, we can use techniques from mean-variance analysis to combine factors. We highlight these differences as we discuss the results. As factors, we use the Fama and French (2015) factors plus the momentum factor.

We begin by highlighting the alpha vs. beta relationship across factors. To do so, we take our 10 portfolios formed using the beta of each factor and we plot the post-formation beta on the factor against the time-series alpha. The results are given in Figure 1. We can see a downward sloping line in each case. That is, higher beta is associated with lower alpha and vice versa. This is not driven by the extreme portfolios and is fairly consistent across factors, though as we see the downward slope is stronger for some factors (e.g., the market and momentum) than it is for others. We next turn to our results which take the low minus high beta portfolio for each factor where the aim is to capture this downward sloping pattern of alphas.

Figure 2 Panel A computes alphas of our univariate beta sorted portfolios. Specifically, we sort all stocks into deciles based on univariate betas with a given factor, and we compute the long minus short portfolio which goes long the low beta group and short the high beta group.[9] We then regress this factor-hedged portfolio on the factor itself and report the alpha. Alphas are positive in each case for all the factors. Economically alphas range from 1% to 10% per year with the average around 6%. Notably large alphas which are economically large and statistically significant include the market, size, momentum and profitability (RMW). The furthest panel on the right plots the information ratio – defined as the alpha per unit of residual standard deviation in the time-series regression. The information ratio has a natural interpretation of how much the hedge factor can increase the Sharpe ratio relative to the original factor. We find information ratios of around 0.3 (ranging from roughly 0.1 to 0.5). Given most factors have Sharpe ratios around 0.3-0.4, these numbers are quite large and comparable to the original factor Sharpe ratios.

Two questions immediately arise. First, how similar are these hedge portfolios across factors? More specifically since we already know that low market beta stocks produce

[9]Note this is similar to the construction of betting-against-beta from Frazzini and Pedersen (2014) but doesn't use leverage

alphas (Frazzini and Pedersen, 2014), are these other sorts really adding much? Second, how does our simple univariate beta sort relate to the characteristic vs covariance debate and the factors formed by Daniel et al. (2017), whose goal is to keep characteristics at a low exposure. We answer these questions by repeating our previous time-series regression but including two additional controls: the betting-against-beta factor from Frazzini and Pedersen (2014), and the DMRS hedge factors which double sort on characteristics and covariances in forming factors. We still include the original factor in the regression as well.

We find that our main results hold even when controlling for these factors. We show these results in Figure 2 Panel B. The alpha on the market hedge portfolio now becomes zero – this is almost by definition because we are controlling for the betting-against-beta factor from Frazzini and Pedersen (2014) who form beta sorted portfolios using the market portfolio. However, aside from the market, the other hedge portfolio alphas are generally positive and significant. One exception to this is the size factor where the alpha disappears, but the value and investment factor alphas both increase and now become significant. This highlights that our portfolios are quite different from just the market CAPM low beta anomaly, and also that they are different from the results found in Daniel et al. (2017) even if they appear similar in spirit.[10] To see the empirical differences from Daniel et al. (2017), note that they form their factors by conditioning jointly on characteristics and covariances – specifically, they assume expected returns are linear in characteristics and that, conditional on the characteristics, there is no relation between beta and expected return. To form their portfolios they first fix the characteristic (e.g., take stocks which have the same book-to-market ratio) and then look for low and high beta stocks with the same value of the characteristic to form hedges. We do not assume any conditional relationship between these two nor do we try to separate characteristics from the

[10]We thank Daniel et al. (2017) for providing their data.

factor beta. Instead, we hedge against betas ignoring characteristics completely which is conceptually (and as we show, empirically) a different exercise. Our positive alphas suggest that beta and expected return fail to line up even when beta and characteristics are related. In addition to these differences, Daniel et al. (2017) also avoid additional exposures such as industry which drive returns but are likely not priced, thus achieving even larger increases in Sharpe ratios. Thus, our results complement the results in Daniel et al. (2017) who also show their method produces quite large Sharpe ratios.

Multivariate factors

We find it illuminating to study the results factor by factor to show that the basic result is pervasive. However, it is also important to consider the factors jointly. To do this, we form a single linear combination of the factors which contains all of their pricing information. Specifically, we compute the ex-post mean-variance efficient combination of the factors which we call r^* ($r^* = b'F$ where $b = \Sigma^{-1}\mu$ is chosen to maximize the Sharpe ratio of r^*).

We repeat our same exercise by forming 10 beta sorted portfolios, sorted on betas with respect to r^* instead of an individual factor. Importantly, we emphasize that, unlike all of our other results, not tradeable because these weights are chosen using the full sample, hence an investor forming betas with respect to r^* could not do so in real time without knowing these weights. For our purposes, this is fine as we use this to illustrate our point about pervasively high expected returns for low beta stocks. In fact, we argue that the full sample estimation of r^* provides a higher hurdle – because this is the *ex-post* MVE portfolio, it will if anything be harder to improve Sharpe ratios with respect to this factor and thus more difficult to find alpha.

We consider different constructions of r^* using different combinations of factors F. The results are documented in Figure 3. We again find pervasively large alphas on low minus high exposure portfolios. These results generally hold when we only control for

r^* as a factor, as well as when we control for BAB and the DMRS portfolios (Panel B). These results highlight that the ability to hedge factor risk at seemingly low cost holds for even the mean-variance efficient combinations of factor models that summarize all of their pricing information. Further, the results go well beyond the standard flat slope of the CAPM market line.

2.3 Minimum variance portfolio

We now use our results to construct a minimum variance portfolio that treats all expected returns as constants and does mean variance optimization with the goal of reducing risk through the covariance matrix. The idea here is analogous to the approach in Moreira and Muir (2017), who form portfolios assuming that there is no risk-return trade-off in the time-series. Here, the focus on minimum-variance portfolios implicitly assumes that there is no risk-return trade-off with respect to variation in volatility driven by variation in factor exposures. This is the optimal portfolio for a mean-variance investor only if the expected-return-beta slope studied above is perfectly flat. However, we show in Section **??** that it is generally true that the optimal mean-variance portfolio is a combination of r^* and the minimum-variance portfolio (MVP) with the weight on the MVP increasing on the flatness of the expected-return-beta slope.

To construct our portfolios at month t, first we compute betas relative to a set of factors F using daily data for the previous 36 months. That is, we regress stock i's returns on asset pricing factor F:

$$R_{i,\tau} = a_{i,t} + \beta'_{i,t} F_\tau + \varepsilon_{i,\tau},$$

where τ represents a day in the 36-month window from month $t-36$ to month $t-1$, and F_τ is a column vector of pricing factors. In our empirical exercise, we use different factor models and therefore the vector F_τ is specified accordingly. We require a minimum of 100 observations to run these daily regressions.

The second step is to construct a proxy for variance-covariance matrix of all returns:

$$\Sigma_t \equiv B_t \Omega_t B_t' + S_t,$$

where B_t is matrix whose i^{th} row is given by the estimated $\beta_{i,t}'$, Ω_t is the estimated variance-covariance matrix of F_τ compute from the 36-month window of daily data, and S_t is a diagonal matrix with the estimated variance of the residuals from the regressions. The third and last step is to compute the mean-variance efficient portfolio weights assuming that all assets have the same expected return and that Σ_t is the variance-covariance of all assets. Specifically, the vector with portfolio weights is given by:

$$\omega_t = \frac{1}{\mathbf{1}'\Sigma_t^{-1}\mathbf{1}} \mathbf{1}'\Sigma_t^{-1},$$

where $\mathbf{1}$ is a column vector of ones. The key here is the assumption that the variance-covariance matrix has a factor structure given by the factors we selected.

Hence, we compute the portfolio weights, $\omega_t = (\omega_{i,t})_i$, every month using daily returns data from month $t-36$ to month $t-1$. We form our low risk portfolio using monthly data and using ω_t as portfolio weights, that is,

$$R_t^{\text{Low Risk}} = \sum_i \omega_{i,t} R_{i,t}.$$

In Table 4 we form minimum variance portfolios based on various combinations of the factors and look at their risk-return properties. We find very large annualized Sharpe ratios of around 0.8 for these minimum variance portfolio despite the fact that they reduce their factor exposures dramatically – they do not take advantage of characteristics or expected return dispersion in any way. Instead they only seek to avoid factor exposure.

In Table 5 studies alphas of these minimum variance portfolio with respect to various factor models that include the CAPM, Fama-French three factors, and the Fama-French 5 factor model plus momentum. We see positive, statistically significant alphas that persist even when controlling for all of these factors.

In Table 6 we redo this alpha exercise with one change: we replace the value weighted market portfolio with an equal weighted one. In many respects this is a more reasonable, because we optimize pretending that all expected returns are the same across stocks. If we ignore any information we learn about the covariance matrix of returns, the default would be to equal weight all stocks as a mean-variance investor. More generally, there is nothing in our procedure here that tends us toward value-weights, hence we possibly have a large alpha because we may be close to equal weighting rather than because we minimize risk. Therefore, the equal-weighted portfolio is also a tougher benchmark for us. By controlling for the equal weighted market (as well as the size factor) we deal with this issue – and we find we still have substantial alpha even in this case.

Taken together – constructing minimum variance portfolios that *ignore* any dispersion in expected returns and *only* seek to reduce exposure to common risk factors produces large alphas. The intuition is similar to our earlier results that these factor exposures are not fully priced, meaning one can reduce risk with little sacrifice in return.

3. Conclusion

This paper shows that standard risk factors can be hedged at low or no cost. We first show this for macroeconomic factors such as industrial production, unemployment, and default risk indicators, all of which are strongly correlated to both the business cycle. By hedging these factors, we show that we also hedge consumption and GDP, and produce portfolios that – on average – do *well* rather than poorly in recessions. We combine these factors with the aggregate stock market and show that we reduce recession risk but keep average returns. Next, we hedge "reduced form" asset pricing factors such as value, momentum, and profitability – and again show that such hedges have zero or low cost. Because of this, the low beta versions of the reduced form factors have strong positive alphas on the factors themselves – they have roughly similar average returns but low factor betas. The main fact in this paper is that all of these factors (both reduced form and macro) can be hedged out of a portfolio with a minimal cost in terms of expected returns. This has important implications both for optimal portfolio formation and for understand the economic mechanisms for generating risk premiums.

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4. Tables and Figures

Table 1: Macro Hedged Portfolios. See text for details.

Panel A: Hedge Portfolios

	Mkt.	Industrial Production			Initial Claims			Credit	Slope
		1 mth.	3 mth.	6 mth.	1 mth.	3 mth.	6 mth.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Avg. Return	–	1.23	−2.86	−1.24	3.02	−0.11	1.42	0.78	0.84
t-stat.	–	0.63	−1.27	−0.54	1.22	−0.03	0.49	0.35	0.41
Volatility	–	17.99	20.85	21.12	16.58	20.85	19.43	20.43	15.58
Sharpe ratio	–	0.07	−0.14	−0.06	0.18	−0.01	0.07	0.04	0.05
Post-formation β	–	−4.03	−5.39	−2.22	−1.25	−1.61	−0.65	−1.17	−0.15
t-stat.	–	−3.69	−10.35	−6.19	−2.37	−4.43	−2.81	−8.57	−2.38

Panel B: Market Plus Hedge

	Mkt.	Industrial Production			Initial Claims			Credit	Slope
		1 mth.	3 mth.	6 mth.	1 mth.	3 mth.	6 mth.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Avg. Return	7.83	9.39	5.66	7.48	9.39	6.27	7.87	8.95	7.36
t-stat.	4.00	4.14	2.75	3.62	3.48	2.17	2.81	4.64	2.86
Volatility	18.60	20.97	18.97	19.04	18.05	19.32	18.68	17.80	19.71
Sharpe ratio	0.42	0.45	0.30	0.39	0.52	0.32	0.42	0.50	0.37
Pre-hedge exposure	–	5.05	4.63	2.21	1.23	1.43	1.09	1.13	0.05
t-stat.	–	4.63	10.45	7.61	2.68	5.73	6.42	9.33	0.87
Post-hedge exp.	–	0.44	−1.15	−0.25	−0.18	−0.00	0.48	−0.07	−0.12
t-stat.	–	0.35	−2.31	−0.75	−0.31	−0.00	2.18	−0.54	−1.46

Panel C: Macro Risk of Market Plus Hedge

	Mkt.	Industrial Production			Initial Claims			Credit	Slope
		1 mth.	3 mth.	6 mth.	1 mth.	3 mth.	6 mth.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Recession	−29.56	−21.18	−19.78	−16.78	−21.45	−14.74	−16.24	−12.17	−15.56
t-stat.	−5.94	−3.40	−3.49	−2.93	−2.72	−1.74	−1.98	−2.30	−2.05
1-quarter Δc	1.22	0.98	0.06	−0.28	0.78	−0.53	−1.26	−0.10	−0.66
t-stat.	2.06	1.21	0.08	−0.35	0.73	−0.45	−1.15	−0.14	−0.64
1-year Δc	1.04	0.94	0.79	0.64	1.17	0.47	0.36	0.74	0.39
t-stat.	3.98	3.14	2.02	1.94	2.42	0.79	0.78	2.40	1.13
1-quarter Δgdp	0.89	0.61	−0.37	−0.04	1.68	0.18	−0.02	−0.13	0.16
t-stat.	1.74	0.88	−0.57	−0.05	1.93	0.19	−0.02	−0.23	0.19
1-year Δgdp	1.03	0.76	0.60	0.76	0.98	0.42	0.66	0.45	0.63
t-stat.	5.38	3.45	2.02	3.01	2.03	0.88	1.51	1.74	1.81
1-year Δc_{PJ}	1.61	0.84	1.10	1.07	2.33	0.59	0.15	0.27	−0.33
t-stat.	3.91	1.24	1.79	1.43	2.07	0.54	0.14	0.50	−0.34
1-year Δc_{Q4}	3.64	3.32	2.82	1.94	6.18	3.48	2.15	2.94	1.52
t-stat.	2.52	1.77	1.48	0.83	2.51	1.43	0.89	1.80	0.71
1-year Δc_{unfil}	1.13	0.88	1.03	0.84	2.58	1.56	0.40	0.49	0.51
t-stat.	2.15	1.24	1.58	1.07	1.90	1.19	0.30	0.88	0.43
1-year ΔDiv	0.81	0.41	0.48	0.51	0.38	0.03	0.27	0.18	0.52
t-stat.	7.22	2.38	3.02	2.66	1.74	0.15	1.33	1.28	2.52
1-quarter ΔProfit	7.44	−6.36	−12.13	−3.15	−12.16	−9.40	−3.22	−5.32	3.15
t-stat.	1.16	−0.73	−1.50	−0.36	−1.37	−0.96	−0.36	−0.74	0.33
1-year ΔProfit	8.43	1.08	0.11	5.92	−5.66	−5.73	6.78	1.39	3.71
t-stat.	2.53	0.19	0.02	1.24	−1.05	−1.32	1.22	0.39	0.86

Table 2: Asset Pricing Tests of Macro Beta Portfolios. We run $E[R_i] = \lambda_0 + \lambda_1 \beta_{i,f}$ where $\beta_{i,f}$ is computed using a time series regression of returns on each factor. Test assets are 10 beta sorted portfolios based on each factor. We report the intercept λ_0 and the price of risk λ_1 with associated t-stats below. T-stats correct for beta estimation using the Shanken correction. Finally, we report $\lambda_0/E[R]$ which gauges the size of the intercept left over as a fraction of the average of all portfolio test assets used. When this number is near 1, it implies to slope of the beta line with respect to expected returns is flat.

	Industrial Production			Initial Claims			Credit	Slope
	1 mth.	3 mth.	6 mth.	1 mth.	3 mth.	6 mth.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_0	8.79	6.85	7.01	7.19	6.86	8.27	8.73	6.96
t-stat.	4.78	3.82	4.05	3.43	2.76	2.08	5.63	3.52
λ_1	−0.00	0.00	0.01	−0.00	−0.00	−0.01	−0.00	−0.02
t-stat.	−0.19	1.14	1.25	−0.27	−0.02	−0.26	−0.06	−0.16
Adj. R^2	−0.10	0.81	0.58	−0.07	−0.12	−0.06	−0.12	−0.05
$\lambda_0/E[R]$	1.03	0.75	0.73	1.07	1.01	1.18	1.01	1.01

Table 3: Asset Pricing Tests of Existing Factors on Macro Beta Portfolios. We run $E[R_i] = \lambda_0 + \lambda_1 \beta_{i,f}$ where $\beta_{i,f}$ is computed using a time series regression of returns on each factor. The factors we use are long run consumption over three years (Parker and Julliard, 2005), fourth quarter consumption growth (Jagannathan and Wang, 2007), and unfiltered aggregate consumption (Kroencke, 2017), all of which have been shown to be priced on the Fama-French 25 size and book-to-market portfolios. We study the pricing of these factors on the FF25 portfolios used in previous studies (first column) compared to using our 10 beta sorted portfolios as test assets. We report the intercept λ_0 and the price of risk λ_1 with associated standard errors below (using the Shanken correction).

	FF25	Industrial Production			Initial Claims			Credit	Slope
		1 mth.	3 mth.	6 mth.	1 mth.	3 mth.	6 mth.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parker Julliard									
$\lambda_{0,PJ}$	3.74	10.41	8.36	7.81	6.94	4.94	8.79	9.11	7.05
s.e.	2.76	2.29	2.21	2.28	3.62	3.63	3.52	2.05	2.42
$\lambda_{1,PJ}$	3.26	−0.93	1.05	1.87	0.29	2.09	−1.29	0.33	−0.24
s.e.	1.67	1.33	2.05	1.40	1.61	1.52	1.70	2.26	1.66
R^2	0.31	−0.06	−0.03	0.36	−0.10	0.48	0.01	−0.09	−0.07
Q4-Q4									
$\lambda_{0,Q4}$	3.23	8.51	5.37	7.76	5.13	2.30	7.42	7.26	6.81
s.e.	4.21	2.79	3.53	2.36	4.53	4.67	3.34	2.25	2.95
$\lambda_{1,Q4}$	1.73	0.02	0.88	0.27	0.49	1.10	−0.03	0.33	0.01
s.e.	0.76	0.68	0.79	0.48	0.62	0.80	0.61	0.77	0.74
R^2	0.59	−0.12	0.38	0.21	0.08	0.71	−0.12	−0.02	−0.12
Unfiltered									
$\lambda_{0,unfil}$	5.95	10.64	8.72	7.89	6.96	2.01	7.88	8.71	6.74
s.e.	2.86	2.31	2.16	2.33	4.48	5.12	3.03	2.06	2.50
$\lambda_{1,unfil}$	3.44	−1.30	0.82	1.98	0.12	2.60	−0.28	0.75	0.08
s.e.	1.90	1.22	1.70	1.69	1.36	2.10	1.05	2.67	1.10
R^2	0.24	−0.02	−0.08	0.33	−0.12	0.70	−0.11	0.01	−0.12

Table 4: Mean variance and Sharpe ratio of minimum variance portfolio. We form minimum variable portfolios and compute the mean variance and sharpe. We construct weights as: $w = (b'\Sigma_F b + \Sigma_\varepsilon)$ where b are factor loadings, Σ_F is the factor variance covariance matrix, and Σ_ε is a diagonal matrix of residual return variances. The factor models F are the market (CAPM), Carhart model (Fama-French 3 factors plus momentum), the Fama-French 5 factors, and the FF 5 plus 5 industry portfolios.

	Avg. excess return	*t*-statistic	Sharpe ratio
Mkt	8.05	9.82	0.82
Car	7.46	9.13	0.82
FF5	7.50	9.12	0.82
FF5+ind	7.09	8.82	0.80

Table 5: Alphas of minimum variance portfolio. We form minimum variable portfolios and compute the alpha. The market in this tables is defined as the value weighted return in CRSP.

	CAPM	3FF	3FF+MOM	5FF	5FF+MOM	5FF+MOM+BAB
Mkt Alpha	6.16	6.07	5.66	3.40	3.41	1.93
t-stat.	6.68	6.58	5.97	3.04	3.00	2.00
Info. ratio	0.71	0.71	0.66	0.44	0.44	0.29
Car Alpha	5.70	5.70	5.22	3.73	3.73	2.47
t-stat.	6.65	6.63	5.92	3.47	3.41	2.56
Info. ratio	0.71	0.71	0.65	0.50	0.50	0.37
FF5 Alpha	5.78	5.82	5.29	4.00	4.02	2.73
t-stat.	6.70	6.74	5.98	3.68	3.64	2.80
Info. ratio	0.72	0.72	0.66	0.53	0.53	0.41
FF5+ind Alpha	5.45	5.51	4.98	3.68	3.73	2.51
t-stat.	6.51	6.58	5.81	3.46	3.45	2.61
Info. ratio	0.69	0.71	0.64	0.50	0.50	0.38

Table 6: Alphas of minimum variance portfolio (part 2). We form minimum variable portfolios and compute the alpha. The market in this tables is defined as the *equal* weighted return in CRSP.

	CAPM	3FF	3FF+MOM	5FF	5FF+MOM	5FF+MOM+BAB
Mkt Alpha	6.07	6.24	5.51	3.60	3.19	2.04
t-stat.	6.60	6.82	5.88	3.29	2.87	2.12
Info. ratio	0.70	0.73	0.65	0.47	0.42	0.31
Car Alpha	5.67	5.86	5.09	3.89	3.51	2.54
t-stat.	6.58	6.87	5.83	3.70	3.28	2.64
Info. ratio	0.70	0.74	0.64	0.53	0.48	0.39
FF5 Alpha	5.75	5.98	5.16	4.15	3.80	2.80
t-stat.	6.63	6.97	5.89	3.89	3.51	2.89
Info. ratio	0.71	0.75	0.65	0.56	0.51	0.42
FF5+ind Alpha	5.41	5.67	4.87	3.83	3.50	2.56
t-stat.	6.44	6.81	5.73	3.68	3.31	2.68
Info. ratio	0.69	0.73	0.63	0.53	0.48	0.39

Figure 1: Alphas of beta sorted portfolios. We plot alphas on each individual factor against post-formation betas formed in univariate regressions on each factor. The y-axis is in annualized return units (e.g., 0.1 means 10% per year). We form 10 beta sorted portfolios on each factor individually then value-weight stocks within the deciles. We regress the portfolio returns (in excess of the risk-free rate) on the original factors and plot post-formation betas (x-axis) against the alpha from the time-series regression (y-axis).

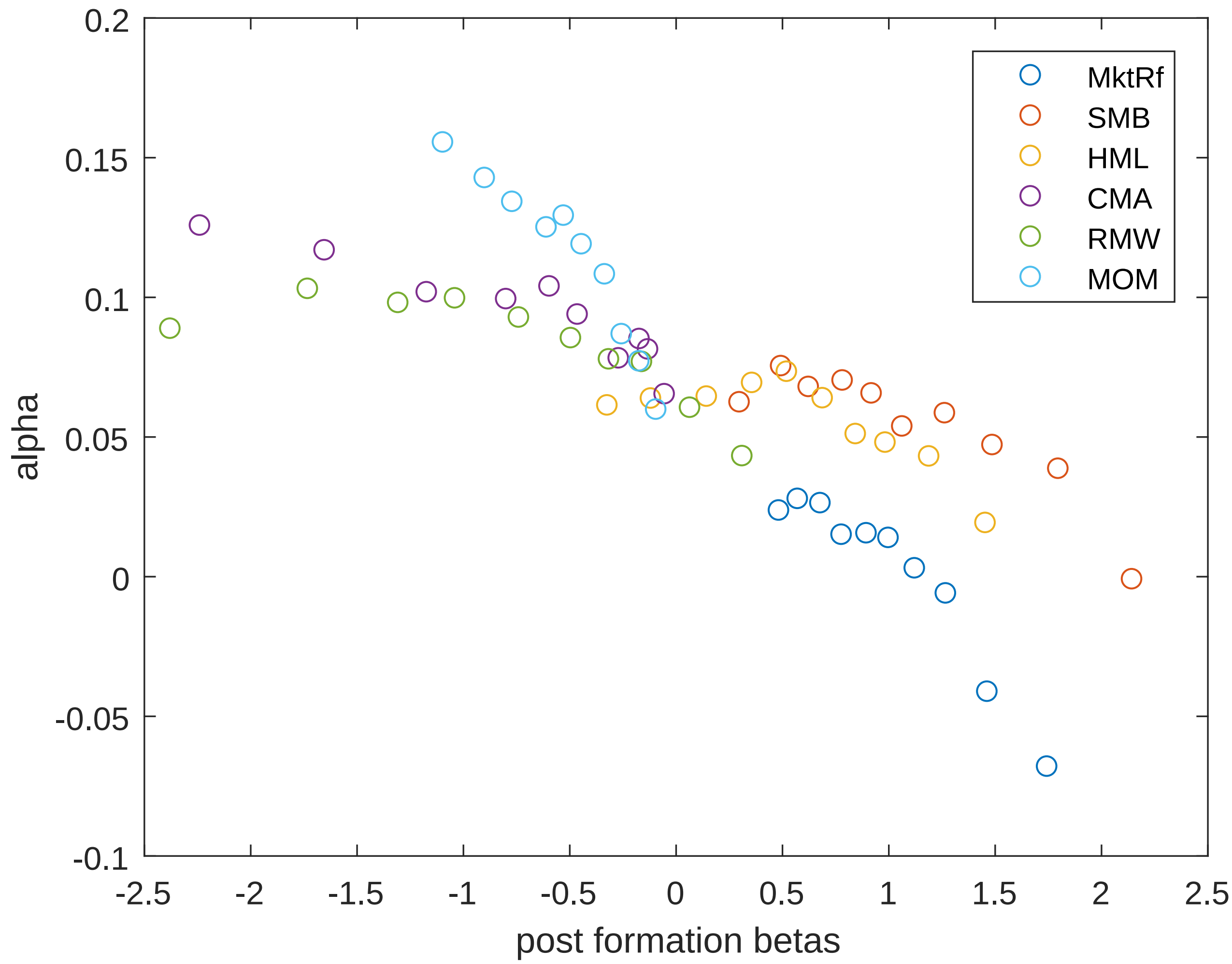
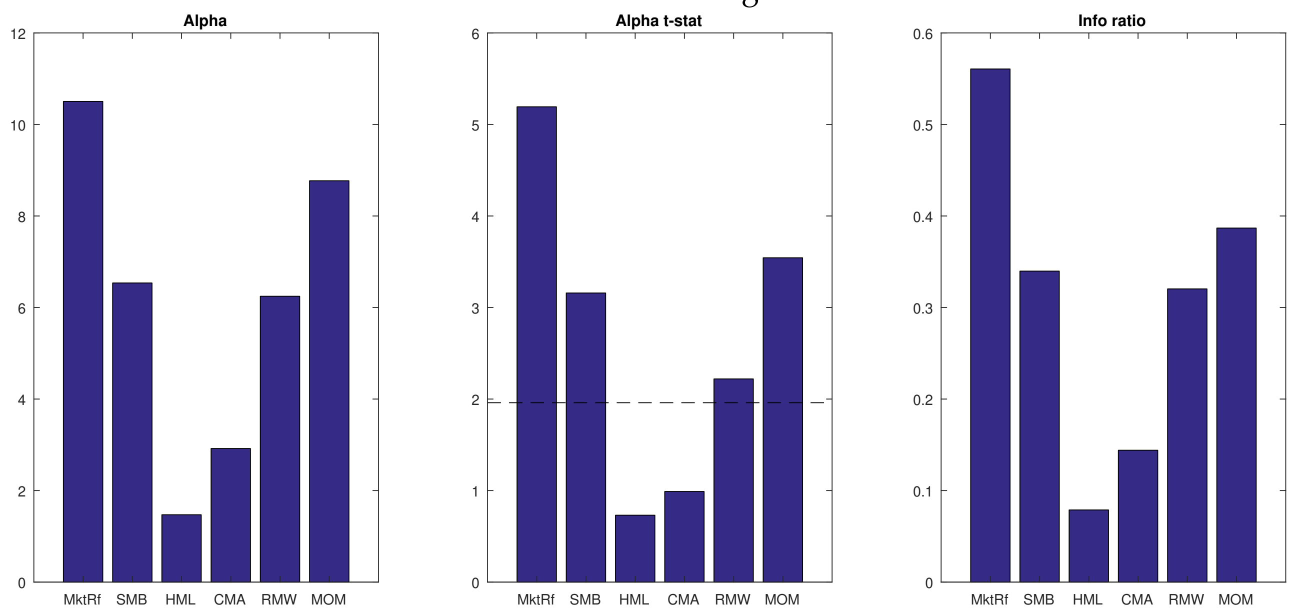


Figure 2: Beta sorted portfolios. We plot alphas on beta sorted portfolios by factor. We sort stocks by their beta with respect to individual factors and then form a beta factor using the low minus high beta portfolio based on pre-ranking beta deciles. The first panel shows the results controlling for the original factor used, the second panel also controls for the BAB (Frazzini and Pedersen (2014)) factor formed only using the market, and the hedge portfolios from DMRS (Daniel et al., 2017).

Panel A: Controls for original factor



Panel B: Controls for factor, Mkt BAB, and DMRS hedge portfolio

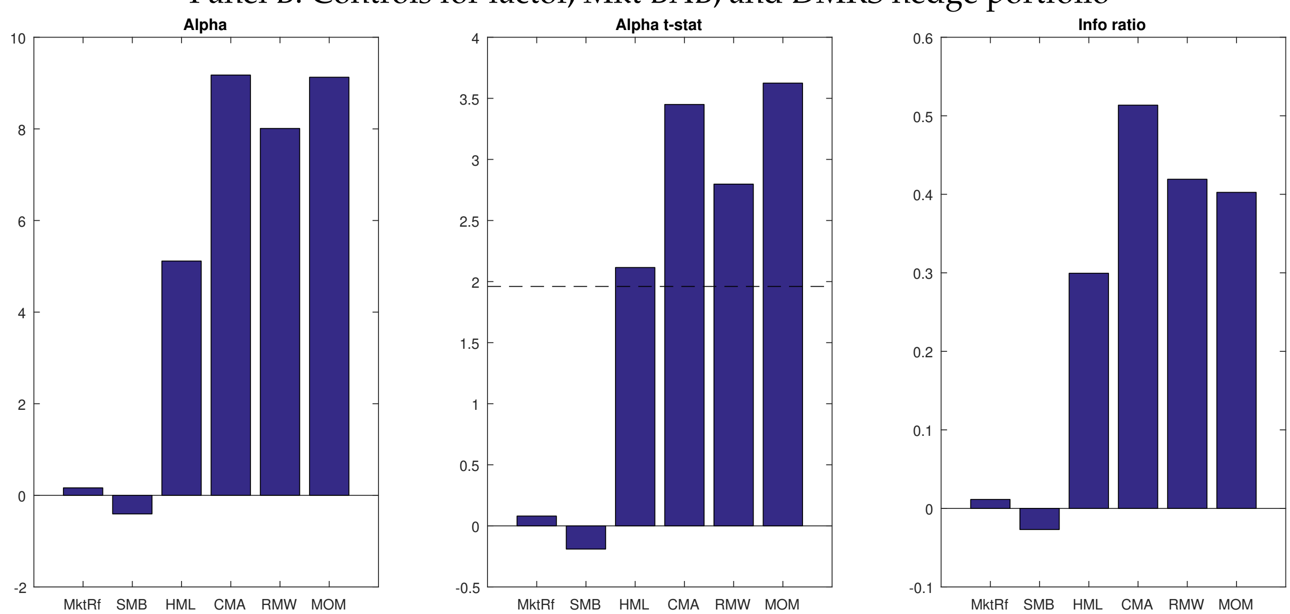
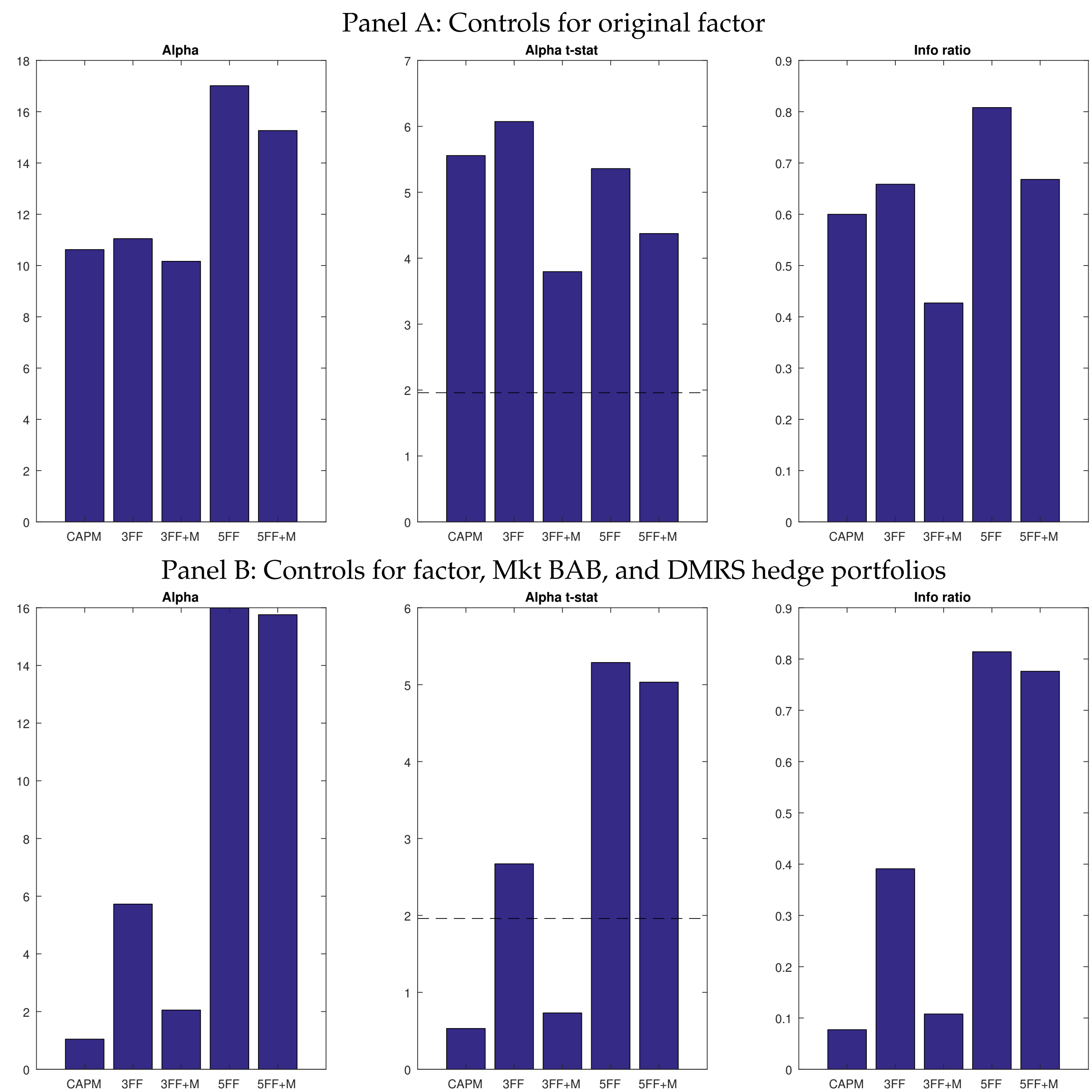


Figure 3: Multi-factor beta sorted portfolios. We plot alphas on beta sorted portfolios with respect to mutifactor benchmark r^*. We repeat the exercise from the last figure, but instead of using single factors to beta sort, we use ex-post MVE combinations of factors (e.g., $b'F$ where F is a set of factors and b is chosen to maximize full sample Sharpe ratios).



Appendix for
"Hedging Risk Factors"

A Additional Tables

Table A.1: Other Macro Hedged Portfolios. We form portfolios that hedge macro risk. See text for details.

Panel A: Hedge Portfolios

	Mkt.	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)	(5)
Avg. Return	–	3.17	0.81	0.47	−2.38
t-stat.	–	0.75	0.36	0.22	−0.53
Volatility	–	21.59	16.51	18.50	23.14
Sharpe ratio	–	0.15	0.05	0.03	−0.10
Post-formation β	–	−0.76	−0.43	−0.03	−0.94
t-stat.	–	−3.91	−1.95	−4.36	−3.61

Panel B: Market Plus Hedge

	Mkt.	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)	(5)
Avg. Return	7.83	10.99	6.81	8.03	5.38
t-stat.	4.00	2.53	2.41	2.62	1.35
Volatility	18.60	22.05	20.54	26.25	20.66
Sharpe ratio	0.42	0.50	0.33	0.31	0.26
Post-formation β	–	−0.46	0.17	0.01	−0.24
t-stat.	–	−2.30	0.61	0.59	−1.00
Market Exposure	–	0.49	0.52	0.04	0.83
t-stat.	–	4.23	2.62	5.33	5.17

Panel B: Market Plus Hedge

	Mkt.	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)	(5)
Recession	−29.56	−42.24	−16.89	−23.18	−13.49
t-stat.	−5.94	−2.72	−2.02	−2.93	−1.04
1-quarter Δc	1.22	1.92	0.03	0.24	−1.89
t-stat.	2.06	0.76	0.03	0.33	−0.88
1-year Δc	1.04	1.13	0.61	0.60	−0.05
t-stat.	3.98	1.18	1.72	1.87	−0.07
1-quarter Δgdp	0.89	3.50	1.13	−0.37	1.84
t-stat.	1.74	1.70	1.24	−0.59	1.02
1-year Δgdp	1.03	0.76	0.70	0.48	−0.07
t-stat.	5.38	1.15	2.13	2.56	−0.13

Table A.2: Asset Pricing Tests of Other Macro Beta Portfolios. We run $E[R_i] = \lambda_0 + \lambda_1 \beta_{i,f}$ where $\beta_{i,f}$ is computed using a time series regression of returns on each factor. Test assets are 10 beta sorted portfolios based on each factor. We report the intercept λ_0 and the price of risk λ_1 with associated t-stats below. T-stats correct for beta estimation using the Shanken correction. Finally, we report $\lambda_0/E[R]$ which gauges the size of the intercept left over as a fraction of the average of all portfolio test assets used. When this number is near 1, it implies to slope of the beta line with respect to expected returns is flat.

	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)
λ_0	9.61	6.07	8.99	7.39
t-stat.	3.42	2.74	3.09	2.75
λ_1	−0.05	0.01	−0.23	0.02
t-stat.	−0.93	0.20	−0.40	0.37
Adj. R^2	0.64	−0.11	0.47	0.22
$\lambda_0/E[R]$	1.20	0.93	1.10	0.87

Table A.3: Macro Hedged Portfolios: quarterly series. We form portfolios that hedge macro risk. See text for details.

Panel A: Hedge Portfolios

	Mkt.	Ind. Production	Initial Claims	Credit	Slope	Cons.	GDP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. Return	–	−0.71	2.58	−1.87	−0.24	3.41	−0.35
t-stat.	–	−0.40	1.01	−1.10	−0.14	1.79	−0.20
Volatility	–	16.25	17.08	15.62	12.83	15.28	14.21
Sharpe ratio	–	−0.04	0.15	−0.12	−0.02	0.22	−0.02
Post-formation β	–	−1.58	−0.27	−0.08	0.05	0.28	−6.04
t-stat.	–	−3.77	−0.87	−1.10	1.94	0.10	−3.10

Panel B: Market Plus Hedge

	Mkt.	Ind. Production	Initial Claims	Credit	Slope	Cons.	GDP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. Return	8.41	8.26	9.29	7.10	6.37	10.77	7.01
t-stat.	3.60	3.10	2.42	2.82	2.23	3.76	2.73
Volatility	22.23	24.49	25.59	23.09	21.77	23.00	20.62
Sharpe ratio	0.38	0.34	0.36	0.31	0.29	0.47	0.34
Post-formation Beta	–	1.40	0.82	0.58	0.06	6.36	−3.02
t-stat.	–	2.18	1.79	5.93	1.37	1.57	−1.05
Market Exposure	–	4.01	1.09	0.73	0.01	4.87	3.56
t-stat.	–	7.97	3.84	11.68	0.42	2.06	1.74

Panel C: Macro Risk of Market Plus Hedge

	Mkt.	Ind. Production	Initial Claims	Credit	Slope	Cons.	GDP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Recession	−25.79	−29.09	−32.88	−25.37	−37.49	−22.39	−17.57
t-stat.	−4.64	−4.22	−3.15	−3.89	−4.93	−2.96	−2.58
1-quarter Δc	1.22	1.36	1.96	1.27	2.70	1.59	0.62
t-stat.	2.06	1.57	1.33	1.70	2.56	1.57	0.68
1-year Δc	1.04	1.34	1.38	0.95	1.42	1.20	1.02
t-stat.	3.98	2.88	3.31	2.84	3.86	3.69	3.31
1-quarter Δgdp	0.89	1.63	0.08	0.50	1.35	0.52	−0.76
t-stat.	1.74	2.18	0.07	0.77	1.58	0.64	−1.05
1-year Δgdp	1.03	1.36	1.28	0.87	1.42	1.04	0.80
t-stat.	5.38	3.82	3.48	3.04	4.42	3.62	3.08

Table A.4: Asset Pricing Tests of Macro Beta Portfolios: quarterly series. We run $E[R_i] = \lambda_0 + \lambda_1 \beta_{i,f}$ where $\beta_{i,f}$ is computed using a time series regression of returns on each factor. Test assets are 10 beta sorted portfolios based on each factor. We report the intercept λ_0 and the price of risk λ_1 with associated t-stats below. T-stats correct for beta estimation using the Shanken correction. Finally, we report $\lambda_0/E[R]$ which gauges the size of the intercept left over as a fraction of the average of all portfolio test assets used. When this number is near 1, it implies to slope of the beta line with respect to expected returns is flat.

	Ind. Production	Initial Claims	Credit	Slope	Cons.	GDP
	(1)	(2)	(3)	(4)	(5)	(6)
λ_0	18.25	26.90	19.93	19.99	17.55	24.30
t-stat.	2.72	2.92	3.09	3.35	2.32	4.41
λ_1	0.01	−0.02	0.04	−0.12	0.00	−0.00
t-stat.	1.59	−0.64	1.10	−0.49	1.00	−0.52
Adj. R^2	0.32	−0.09	0.31	−0.02	0.05	−0.05
$\lambda_0/E[R]$	0.65	1.21	0.70	0.99	0.78	1.04