Hedging Risk Factors

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Abstract

Standard risk factors can be hedged with minimal reduction in average returns. Stocks with low factor-exposure have similar performance relative to stocks with high factor-exposure, hence a long-short portfolio hedges factor risk with little reduction in expected returns. This is true for both "macro" factors relating to the business cycle, and "reduced-form" factors such as value and momentum. Hedging macro factors also hedges business cycle risk (e.g. NBER recessions) and hedges many other macro factors argued to be priced in the literature, and hedging "reduced-form" factors generates large alphas. Our results have implications for portfolio formation and for understanding the economic origins of equity risk premiums.

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This paper shows that standard risk factors can be hedged at low or no cost. We construct portfolios by sorting stocks based on their exposures to macroeconomic factors such as industrial production, unemployment, and default risk indicators. We show that these portfolios not only hedge these factors, but also hedge exposure to consumption, GDP, and many other macroeconomic risk factors at quarterly to yearly frequencies, and produce portfolios that – on average – do *well* rather than poorly in recessions. By targeting business cycle factors that are available at higher frequencies (monthly) we can construct effective real time business cycle hedges. Thus, our hedge portfolios are informative test assets for a number of macroeconomic risk factors shown to be priced in the literature. We show that such hedge portfolios have returns close to zero, and when combined with the aggregate stock market, they reduce business cycle risk and exposure to a variety macroeconomic risk factors without impacting average returns. This sheds light on macroeconomic risks previously shown to explain the cross-section of returns (Parker and Julliard (2005), Jagannathan and Wang (2007), and Kroencke (2017)) and in formal asset pricing tests estimated prices of risk of these factors using our hedge portfolios are near zero, in contrast to previous studies.

Next, we hedge "reduced form" asset pricing factors such as value, momentum, and profitability – and again show that such hedges have surprisingly low cost in terms of reduction in average returns. Because of this, the low beta versions of the reduced form factors have positive alphas on the factors themselves – they have similar average returns but negative 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 understanding the economic origins of risk premiums. We also show that our beta sorted portfolios provide alternative test assets to evaluate existing asset pricing models.

To fix ideas, we start with the standard asset pricing equation in beta representation of an unconditional asset pricing model:

$$E[R_{i,t+1}] = \lambda' \beta_i$$

where $R_{i,t+1}$ is the excess return of any asset i, and $\beta_i = cov(R_{i,t+1}, -m_{t+1})/var(m_{t+1})$

where m is the pricing kernel or stochastic discount factor (SDF) that prices all assets. We use the familiar "beta" representation here for convenience but this is also equivalent to the statement $E[R_{i,t+1}m_{t+1}] = 0$. 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 or recessions. 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. However, there are issues with some of these existing tests assets (see Lewellen, Nagel, and Shanken (2010) for issues with evaluating factor models with these test assets, and Bryzgalova (2017) for issues with having little variation in factor covariances when evaluating models). Instead, we create portfolios that create dispersion in the right hand side, i.e., dispersion in factor exposures, following the portfolio formation techniques in Jensen, Black, and Scholes (1972) and Fama and French (1992). Our insight is not in the methodology of designing these test assets but in showing empirically that they provide informative test assets to evaluate macro and reduce form models because they generate meaningful spreads in post-formation factor exposures.

Specifically, for each factor we form portfolios (e.g., quintiles or deciles) by sorting stocks based on their factor beta over a trailing window. We then value-weight the stocks within each beta-sorted portfolio bucket. 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. 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 post-formation beta on the factor. Importantly, this strong pattern of predictability of post-formation betas is true for both reduced-form and macroeconomic risk factors. We then form hedge portfolios by constructing low minus high beta versions of each factor and find that this resulting portfolio has a reliably 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. Equivalently, there is a relatively "flat" slope of the beta vs expected return of the factors. 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 mismatch between expected return and risk is relevant for the broader economy.[1]

We then combine the macroeconomic hedges with the market return – the idea is to start with the market return as a portfolio that has a high risk-premium and, as we show, very high exposure to macroeconomic risks, and then see how adding the hedge changes the portfolio risk-return profile. Specifically, we evaluate whether our portfolios can reduce market portfolio exposure to macroeconomic risks and at what cost. 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 and their higher frequency time-series (they are available monthly which we show is important to construct effective hedges using our rolling approach). We also combine all macro series into a single series capturing an overall indicator of business cycles. We then show that hedging these higher frequency factors naturally also hedge many macroeconomic

[1] As always, we acknowledge the joint hypothesis problem that any apparent mispricing is only with respect to the existing factor models we consider.

factors that are available at much lower frequency and hence don't lend themselves easily to a beta sorting methodology. In particular, we show that trying to hedge the lower frequency factors directly doesn't work in terms of generating economically large post formation exposures. Intuitively, if one forms rolling five year betas of stocks on a macro factor available annually, there are only five observations resulting in extremely noisy betas. However, monthly factors which track the macro-economy closely can be used to better inform these lower frequency factors.

We start by showing that the market portfolio alone is significantly exposed to these business cycle factors. We then show that adding the hedge portfolio reduces or eliminates these exposures but keeps roughly the same average return. Further, we show that the hedge portfolios help reduce or eliminate market exposure to GDP or consumption risk. The implication is that one could achieve roughly the same expected return and Sharpe ratio as the market with a much lower exposure to the business cycle. This means the explanation for the equity premium can not rely on exposure to these factors alone. Importantly, these portfolios also hedge against many other macro factors that previous work show to be 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 theoretically motivated test assets formed on macro risk exposures is important for evaluating successful macro-based pricing factors since these factors are highly correlated with the business cycle variables that we hedge. We conduct formal asset pricing tests and find all these factors have prices of risk near zero, in contrast to the results in previous studies focusing on portfolios based on size and book to market as test assets. Since our test assets are designed specifically to generate exposure to business cycles, they help overcome issues of weak beta spreads from prior studies (see Bryzgalova (2017)).

Next, we use our macro hedge portfolios to evaluate the contribution of macroeconomic risk to the pricing kernel or stochastic discount factor (SDF). Importantly, we consider that our while our beta sorted portfolios may avoid macroeconomic risk, they may also load on other unobserved priced factors that enter the SDF. Our analysis imply upper bounds on the total SDF volatility that can be driven by macroeconomic risk. Intuitively, if we can hedge all macro risk and maintain a very high Sharpe ratio, then the total volatility of the SDF coming from macroeconomic risk is limited by our views on the maximum volatility of the SDF. Our findings indicate an upper bound of the SDF variance coming from macroeconomic risk of between 3% and 50% depending on which factor model we use. Overall, these results strongly suggests that recession risks explain only a small part of the very high volatility of the stochastic discount factor.

We show the implications of this result as well for the 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 typically 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 et al. (1972), Frazzini and Pedersen (2014)), we show that it is in fact pervasive across factors and our alphas for other factors remain when controlling for the beta anomaly for the market portfolio.[2] In contrast with Frazzini and Pedersen (2014) who focus on equal-weighted portfolios, we focus on value-weighted portfolios. Therefore, the empirical patterns we document have implications that are relevant to a large share of the stock market in terms of market values. Further, our results suggest caution in the typical practical implementation of these models – for example, the models are often used for performance evaluation (e.g., for mutual funds) implicitly assuming higher factor betas should go hand in hand with higher performance which we find is not the case.

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 (unconditional) 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

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

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.[3] We find similar results if we equal weight the factors in the MVE construction instead of using ex-post MVE weights.

Finally, 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. 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 the factors we considered span the mean-variance efficient portfolio or capture all sources of priced risk, this would not be the case, 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 factor 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 average 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

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

– 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 relation 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, and the literature that followed on maximum correlation portfolios (Breeden, Gibbons, and Litzenberger, 1989) and mimicking portfolios (Huberman, Kandel, and Stambaugh, 1987; Lamont, 2001; Balduzzi and Robotti, 2008), is that we focus on portfolios with strong cross-sectional variation in factor betas which we evaluate post-formation. 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., a wide variety of consumption-based factors) 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 analyses macro factors. Section 3 analyses reduced-form risk factors. Section 4 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.[4]

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 24 months. Thus in this case τ represents a day in the two year window from month $t-24$ to month $t-1$ giving roughly 500 daily observations. We require a minimum of 100 observations to run these daily regressions. For macroeconomic factors, which are available monthly, we compute betas by leveraging higher frequency return data compared to lower frequency macroeconomic data to estimate correlations and volatilities separately (see also Frazzini and Pedersen (2014)). Specifically, we compute the correlation ($corr_{i,t}$) between our macro series and returns using the past 10 years (120 months) of monthly data and we require at least 2 years of data (24 observations) to compute correlations. This gives a long time span and results in higher precision due to using more observations. For volatility ($\sigma_{i,t}$), we follow our same choice for the traded factors and compute the volatility of returns over the past two years using daily return data, giving us roughly 500 observations to compute rolling volatility (as before we requite a minimum of 100 observations to compute volatility for returns). We then sort stocks based on the product of return volatility and correlation with the macro factor ($corr_{i,t} \times \sigma_{i,t}$). Note

[4] 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.

that while technically beta also requires the volatility of the macro factor itself, this is common to all stocks, so has no effect on sorting stocks into portfolios, hence any window will give us exactly the same results. Unlike Frazzini and Pedersen (2014) we don't use these preformation betas to weight stocks within portfolio buckets, only to rank them into the buckets at which point we simply value-weight all stocks within the bucket. When we assess post formation betas for macro factors, we revert to standard betas using monthly data on the macro factors. We also find qualitatively similar results if we simply use standard betas using five year rolling regressions in our monthly data, though post formation betas in this case are noisier than what is reported in the main text. Since our goal is to generate large spreads in post-formation betas, we stick to the procedure of estimating the correlation and volatility separately to give more precise estimates.

Notice in addition that we use one extra lag in the case of macro data 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 quintiles (sometimes deciles) based on their factor betas $\beta_{i,t}$. Next, we form a value weighted portfolio of the stocks in each one of the quintiles. We use value weights to avoid influence from small or microcap stocks in the procedure.[5] This procedure forms our beta sorted portfolios and we analyze

[5]One remaining concern is if beta and size are correlated then our quintiles 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 quintile and then value weight across

the returns of these portfolios over a future period.

2. Macroeconomic factors

We motivate our analysis with a perspective from Fama (1991): "In the end, I think we can hope for a coherent story that (1) relates the cross-section properties of expected returns to the variation of expected returns through time, and (2) relates the behavior of expected returns to the real economy in a rather detailed way. Or we can hope to convince ourselves that no such story is possible."

We start by showing that the market portfolio has very large exposures to a variety of macro-economic factors. We then show that we can construct effective real-time macro-economic hedges that reduce much of the macro-economic exposures of the market portfolio. We carefully show that our portfolios are effective hedges in an out-of-sample post-formation/post-estimation sense. We then look at the average returns of these hedge portfolios and the market-hedged-portfolio, i.e., a portfolio that combines the market with our hedge portfolio. We then use these portfolios that were designed to capture macro-economic risk to test some of the most successful macro-based models of the stochastic discount factor. We wrap up this section by developing a simple asset pricing bound that allow us to interpret the economic content of our results in a setting with unobserved risk factors.

2.1 Macro risks in the market portfolio

In Figure 1, we start by regressing the market portfolio on a variety of proxies for macro-economic risk (Panel A). The measures of macroeconomic risk are standardized so that the exposures represent the percentage change in annualized returns associated with a one standard deviation shock in the macro variable. We see that the market portfolio is highly

quintiles we arrive at similar magnitude of alphas as if we equal-weight across quintiles.

exposed to realized macro-conditions. For example, the market portfolio loses about 30% during recessions, has a well estimated beta of 8 with respect to standardized consumption growth, with this exposure growing significantly as more sophisticated proxies are used.

The relationship between the market portfolio and broad macroeconomic risks is also the main lens through which the financial press and practitioners interpret large movements in the value of the stock market relative to the value of government bonds. For example, in a three consecutive days in August of 2019 the Wall Street Journal reported "Stocks, Bond Yields Fall Sharply on Trade Tensions", "U.S. Stocks Waver on Disappointing Manufacturing Data", and "Stocks Climb on Strong Retail Earnings" (Menton and Ostroff, 2019; Banerji, 2019; Gunjan Banerji and Menton, 2019). This connection is also a central component of mainstream financial advice. For example, see Financial Times article "How to recession-proof you investment portfolio" (Riding and Agyemang, 2019) and Blackrock perspective on macroeconomic factors (Ang and Hogan, 2018).

Motivated by these facts and economic theory (Breeden, 1979; Lucas Jr, 1978), the literature focused on trying to connect macro-economic risks with cross-section variation in stock returns. Here the seminal paper is Chen et al. (1986) who provide some evidence that macro-betas are related to variation in average returns. Much of the literature that has followed emphasizes how hard it is to estimate stocks macro-economic exposures, as beta estimates lack persistence and seem to behave more like measurement error. In the language of this paper, the hedge portfolios implied by Chen et al. (1986), and the mimicking portfolio literature that followed, did not hedge well, at least not in a post-formation sense. In the next section, we show that our macro hedge portfolios work well as macroeconomic hedges .

2.2 Macro hedge portfolios

In Tables 1, 2 and 3, we show results for portfolios that hedge macroeconomic risks including industrial production, initial claims (unemployment), credit spreads, and the slope of the term structure. We focus on these factors because they capture well variation in economic activity over the business cycle and are measured at relatively high frequency (monthly). High-frequency (monthly) macro variables is key for our approach to construct hedge portfolios that hedge, i.e., with strong spreads in post-formation betas.[6] Our hedge portfolios are 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 the factor goes down in bad times and up in good times (in other words all factors are constructed to be 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 portfolio is thus always designed to hedge the factor risk by providing insurance against bad times.

To see the results of our macro hedge portfolios more clearly, we also combine all the macro series into a combined macro factor. Specifically, for each estimation window when estimating betas, we standardize all macro series in the estimation window to have zero mean and unit variance, then we take an equal weighted average of all series. We only use industrial production and initial claims at 1 month horizons to avoid redundancy. We then study the exposure of the low minus high beta portfolios. This aggregates our results in one single measure. We show these results in Figures 2-6 which we discuss along our factor specific results.

[6]Note that these are also the factors studied by Chen et al. (1986) as measures of the macroeconomic cycle

2.2.1 Exposures: portfolios that hedge macro risk

In Table 1, we begin by documenting the 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, we also 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. To evaluate the economic significance of the hedges our macro hedge portfolios provide we compare the post-formation beta of the market with the port-formation beta once the hedge portfolio is added to the market. We find that factor exposures drop to nearly 0. That is, our portfolios have a spread in betas of the same magnitude as the market exposure to these risks and adding our hedge portfolio eliminates the factor risk completely from the market.

In Table 2, 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 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,

[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.

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.

Figure 2 shows these results for our combined-macro hedge portfolio, where we see exactly the same pattern even more clearly. Figure 4 compares the performance of the hedged-market portfolio around last few recessions. We see that our hedge portfolios were effective in reducing the market exposure to these recession episodes.

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. Figure 3 shows these exposures for our combined macro portfolio. Again, we see that our macro-hedge portfolio provides an effective hedge to these classic factors.

2.2.2 Average returns: the cost of hedging macro risk

In Table 3 Panel A, we see the annualized average returns of this hedge factor. The average returns are generally near zero (statistically and economically). In fact, the average

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

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. In Table 3 Panel B, we again look at the combination of the hedge portfolio with the value weighted market portfolio. The 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). 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. Figure 5 compares the premium on the market with market-hedged portfolio, now build using our combined-macro portfolio. The pattern is again the same. The hedge portfolios earning zero average excess return and the market-hedge portfolio earns exactly the same average return as the market portfolio.

Note that here the fact that the Sharpe ratio did not decrease sharply is the "dog that did not bark", where the "dog" here is macroeconomic risk. Because these portfolios hedge out a variety of macroeconomic risks, the fact that the Sharpe ratio on the market portfolio did not go down when combined with them indicates that macroeconomic risks do not have a high price of risk, or alternatively, it indicates that an investor that cares about macroeconomic risks can capture the entire equity risk premium while at the same time hedging out much of the macroeconomic risks associated with an investment in the market portfolio.

An alternative, perhaps more standard way, of showing that these macroeconomic risks are not strongly priced, is to follow the Fama and MacBeth (1973) approach: 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 report 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 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, they are simply a more formal way to recast our results on average returns and exposures. 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 these factor essentially for free. This is interesting not because we expect these factors in particular to be priced, but, as we show, they proxy for macroeconomic risks more broadly, for example recessions, so these portfolios are likely to be informative about the price of risk of macro-factors more broadly.

2.3 Revisiting Priced Macro 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 5 and Figure 6. 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 for both the individual factors (results in Table 5) and for the combined-macro factor (Results in Figure 6). 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.

2.4 Additional analysis

In Appendix A we run a number of robustness checks and present many additional results. We considers other macro factors as priced sources of risk including luxury consumption, NVIX, and the TED spread and shows similar results to what we document in the main text when considering these factors as well. Second, it considers intermediary-based factors for the cross-section. Third, it examines our macro hedged portfolios when we control for market betas and also double sort based on market betas and our macro factor betas to assess the overlap between market betas and macro betas. Overall the results are quantitatively similar and lead us to the same conclusion that one can reduce or eliminate macro-economic risks with almost no reduction in expected returns.

2.5 Implications for the stochastic discount factor

We now study whether the macro-hedged portfolios we constructed can place bounds on the contribution of macroeconomic risk for the volatility of the stochastic discount factor (sdf). Our analysis so far approached this question from the perspective single-factor consumption models (Parker and Julliard, 2005; Jagannathan and Wang, 2007; Kroencke, 2017). Because these models predict that the sdf should depend only on a single factor, the risk-properties of the hedge portfolio are directly informative about the model,e.g. if a portfolio that hedges out exposure to the factor has a negligible premia, then this factor cannot be the driver of the high sdf volatility observed in the data.

An alternative way of approaching the data is to ask how much of the volatility of the sdf can be traced back to macroeconomic risk, instead of testing if all the sdf volatility is explained by a single macroeconomic factor. We now explore what our hedge portfolios can teach us in this case.

Let's consider an sdf of the following form $m_t = 1 - b_z z_t - b_f f_t$, where f is an unobserved risk-factor and z is an observed macro-factor. Both are normalized here to have zero mean. Motivated by our empirical analysis, consider a hedging portfolio for the macro-factor z, $R_t^z = -z_t + \epsilon_{z,t}$. The portfolio is constructed to perfectly hedge the macro factor. One can think of our empirical procedure in Section 2 as constructing these hedging portfolios. In addition to assuming we can measure macro-risk with our factor z, we also assume that we know the total volatility of the sdf σ_m. Given these assumptions we have that the sdf volatility has the following decomposition,

$$\frac{b_z^2 \sigma_z^2}{\sigma_m^2} + \frac{b_f^2 \sigma_f^2}{\sigma_m^2} = 1. \tag{1}$$

While portfolio R_t^z has a beta of -1 with respect to the macro risk-factor of interest, it does not have a correlation of 1, i.e. the hedge portfolio has some basis risk captured by $\epsilon_{z,t}$. This basis risk could potentially be exposed to the unobserved factor f clouding our inferences about the price of macro-risk b_z. Formally $\epsilon_{z,t} = \beta_{z,f} f_t + \varepsilon_{z,t}$, where $\beta_{z,f}$ is unknown since f_t is an unobserved factor. Intuitively, the zero risk premium of the hedge portfolio R^z could be consistent with a high risk-premium for recessions if the basis risk of the hedge portfolio has a large exposure to the omitted factor f.

Lets say we have an asset with returns R^i such as the market portfolio that has Sharpe ratio μ^i / σ^i and exposure $\beta_{i,z}$ to macro risk. The market-macro-hedged portfolio is then

$R_t^{i,-z} = R_t^i + \beta_{i,z} R_t^z$. By construction $R^{i,-z}$ has zero exposure to macro risk captured by factor z, therefore it must be that it Sharpe ratio is a lower bound on the Sharpe ratio of the unobserved factor:

$$
\begin{aligned}
E[m_t R_t^{i,-z}] &= 0 \qquad (2) \\
\left| \frac{E[R_t^{i,-z}]}{\sigma(R_t^{i,-z})} \right| &\leq |b_f| \sigma(f_t) \qquad (3)
\end{aligned}
$$

The lower bound on the Sharpe ratio due to the unobserved factor together with a bound on the maximum Sharpe ratio, i.e. the sdf volatility, allow us to place an upper bound on the share of the sdf volatility due to macro risk:

$$
\frac{b_z^2 \sigma_z^2}{\sigma_m^2} = 1 - \frac{b_f^2 \sigma_f^2}{\sigma_m^2} \leq 1 - \frac{\left(\frac{E[R_t^{i,-z}]}{\sigma(R_t^{i,-z})} \right)^2}{\sigma_m^2} \qquad (4)
$$

Intuitively, if a portfolio that is macro-hedged gets close to the maximum Sharpe ratio in the economy, so that $\left(\frac{E[R_t^{i,-z}]}{\sigma(R_t^{i,-z})} \right)^2 / \sigma_m^2$ is close to 1, without being exposed to macro risk, then the contribution of macro risk to the sdf must be small. While one could this procedure for any reference portfolio R^i, note that the bound will be tighter, and therefore more informative, the closer asset R^i is to the tangency portfolio.

2.5.1 An upper bound for the pricing implications of recession risk

We now apply this approach to bound the asset pricing implications of recessions. We start from alternative reference portfolios as proxies for the tangency portfolio, and use our hedge portfolio to eliminate recession exposure from the reference portfolio. This gives us $R^{i,-z}$. We then construct a proxy for the sdf volatility by computing the Sharpe ratio of the mean-variance-efficient combination of the reference portfolio and the macro-hedge portfolio. We then use Equation (4) to construct an upper bound for the share of sdf variance due to recessions, which emphasizes the relative importance of recession risk for pricing. We also look at absolute pricing implications by looking at an upper bound to the Sharpe ratio due to recession risk.

Table 6 shows the results using as reference portfolios the market portfolio, the mve combination of the Fama-French three factor model, the mve portfolio associated with the four factor Carhart model, the mve portfolio associated with the Fama-French five factor model, and finally the mve associated with six factor model that adds momentum to the Fama-French five factor model. We see that the bound on recession share of the sdf variance ranges from 50% to 3% depending on the reference portfolio. Note that the much lower "recession share" obtained once we add the profitability and investment factors. While we expect to obtain tighter bounds once we move closer to the tangency portfolio, in this case this pattern is entirely due to the shorter sample available for these factors. For example, if we compute the "recession share" implied by the market portfolio only using the sample for which these factors are available (pos-1963), we obtain a recession share of 8%. Similarly, we find 10% for the FF3 model and 1% for the Carhart model.

Overall, these results strongly suggests that recession risks explain only a small part of the very high volatility of the stochastic discount factor.

3. Reduced form 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.

3.1 Univariate factors

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 7. 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 8 Panel A computes alphas of our univariate beta sorted portfolios. Specifically, we sort all stocks into quintiles 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. This is similar to the construction of betting-against-beta from Frazzini and Pedersen (2014) but doesn't use leverage and uses value-weighting within portfolios, hence our results are more similar to the construction in Novy-Marx (2018). We choose the more standard value-weighting approach to keep our analysis simple and be more comparable to standard portfolio construction methods. 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 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 8 Panel B. The alpha on the market hedge portfolio now disappears – this is almost by definition because we are controlling for the betting-against-beta factor from Frazzini and Pedersen (2014) who form related 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.[9] In reported results we also find that the Daniel et al. (2017) portfolios have alpha relative to our hedge portfolios, so these results say that our portfolios are empirically different than their, but not necessarily better. 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 factor beta. Instead, we hedge against betas ignoring characteristics completely. Conceptually our portfolio construction approach is designed to test the more basic question whether variation in the model notion of risk – factor betas– are priced unconditionally.

While Daniel et al. (2017) use of characteristics can arguably provide a more statistically powerful test of a model, we think our approach has several attractive features. First, it can be implemented for any factor consistently, and not only characteristic-based factors. This means it can always be used to construct empirically useful test assets to evaluate any factor model. Second, it always tests the models in an ”economically” relevant dimension. This is important, since it is arguably the case that all models are likely to be rejected with enough data. We think the relevant bar is whether a model helps us understand something better. And that is exactly what our tests do as they ask if the models can at least price portfolios that were designed to be exposed to the risks that this model predicts to be important. Third, we think our approach is interesting from the perspective of a “model user”. For example, an investor that is using a specific factor

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

model to risk-adjust different mutual funds is implicitly assuming that if they were to implement a portfolio of similar factor exposure as the mutual fund, they would earn the proportional factor premium. If a factor model fails our test, this assumption is invalid, and will drive the investor to overvalue managers that allocate to low beta stocks. A factor model that passes our "hedging" test has the attractive feature that it cannot be beaten by a manager without the use of additional conditional information. So we think a model that passes our test is useful even if it can be rejected by more sophisticated approaches such as developed in Daniel et al. (2017).

3.2 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 9. 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.

One concern is that an investor could not construct these MVE in real time. But note here that we are controlling for the MVE portfolio as well. So the look-ahead bias in the MVE-weight combination is both in the left and the right-hand side of our regression. Nevertheless, to address this concern, we also look at equal-weighted combinations of these factors in Figure 10. The picture that emerges is largely the same.

3.3 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, 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, we follow our general approach for traded factors. First we compute betas relative to a set of factors F using daily data for the previous

24 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 24-month window from month $t-12$ 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 12-month window of daily data, and S_t is a diagonal matrix with the estimated variance of the residuals from the regressions. Importantly, here we screen out small stocks by dropping stocks with a market capitalization below the the bottom 20% of the NYSE market capitalization distribution. Because this procedure is obviously inconsistent with using value-weights, this screening is important to guarantee that our results are not driven by hard-to-trade small stocks.

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 $t-24$ 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 7 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 8 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 9 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.

4. 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.

References

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *The Journal of Finance* 69, 2557–2596.

Ait-Sahalia, Yacine, Jonathan A Parker, and Motohiro Yogo, 2004, Luxury goods and the equity premium, *The Journal of Finance* 59, 2959–3004.

Ang, Andrew, and Ked Hogan, 2018, Macroeconomic factors: important diversifiers.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, 2016, Measuring economic policy uncertainty, *The quarterly journal of economics* 131, 1593–1636.

Balduzzi, Pierluigi, and Cesare Robotti, 2008, Mimicking portfolios, economic risk premia, and tests of multi-beta models, *Journal of Business & Economic Statistics* 26, 354–368.

Banerji, Gunjan, 2019, Stocks, bond yields fall sharply on trade tensions, *The Wall Street Journal* August 23.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 45, 444–455.

Breeden, Douglas T., 1979, An intertemporal asset pricing model with stochastic consumption and investment opportunities, *Journal of Financial Economics* 7, 265–296.

Breeden, Douglas T, Michael R Gibbons, and Robert H Litzenberger, 1989, Empirical tests of the consumption-oriented capm, *The Journal of Finance* 44, 231–262.

Bryzgalova, Svetlana, 2017, Spurious factors in linear asset pricing models, Working paper, Stanford University.

Campbell, John Y., and John Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383–403.

Daniel, Kent, Lira Mota, Simon Rottke, and Tano Santos, 2017, The cross section of risk and return, *working paper* .

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* 52, 1–33.

Fama, Eugene F., 1991, Efficient capital markets: Ii, *The Journal of Finance* 46, 1575–1617.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–65.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 113, 607–636.

Frazzini, Andrea, and Lasse H. Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

Greenwald, Daniel L., Martin Lettau, and Sydney C. Ludvigson, 2014, Origins of stock market fluctuations, Working Paper 19818, National Bureau of Economic Research.

Gunjan Banerji, Avantika Chilkoti, and Jessica Menton, 2019, Stocks climb on strong retail earnings, *The Wall Street Journal* August 21.

Harvey, Campbell R, Yan Liu, and Heqing Zhu, 2016, ...and the cross-section of expected returns, *The Review of Financial Studies* 29, 5–68.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

Huberman, Gur, Shmuel Kandel, and Robert F Stambaugh, 1987, Mimicking portfolios and exact arbitrage pricing, *The Journal of Finance* 42, 1–9.

Jagannathan, Ravi, and Yong Wang, 2007, Lazy investors, discretionary consumption, and the cross-section of stock returns, *The Journal of Finance* 62, 1623–1661.

Jensen, Michael C, Fischer Black, and Myron S Scholes, 1972, The capital asset pricing model: Some empirical tests, *Studies in the Theory of Capital Markets* .

Kelly, Bryan, Seth Pruitt, and Yinan Su, 2018, Characteristics are covariances: A unified model of risk and return, Working paper, National Bureau of Economic Research.

Kroencke, Tim A, 2017, Asset pricing without garbage, *The Journal of Finance* 72, 47–98.

Lamont, Owen A, 2001, Economic tracking portfolios, *Journal of Econometrics* 105, 161–184.

Lettau, Martin, and Sydney Ludvigson, 2001, Consumption, aggregate wealth, and expected stock returns, *the Journal of Finance* 56, 815–849.

Lettau, Martin, and Sydney C. Ludvigson, 2009, Euler equation errors, *Review of Economic Dynamics* 12, 255 – 283.

Levi, Yaron, and Ivo Welch, 2017, Market-beta and downside risk, *working paper* .

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194.

Lucas Jr, Robert E, 1978, Asset prices in an exchange economy, *Econometrica: Journal of the Econometric Society* 1429–1445.

Manela, Asaf, and Alan Moreira, 2017, News implied volatility and disaster concerns, *Journal of Financial Economics* .

Menton, Jessica, and Caitlin Ostroff, 2019, U.s. stocks waver on disappointing manufacturing data, *The Wall Street Journal* August 22.

Moreira, Alan, and Tyler Muir, 2017, Volatility-managed portfolios, *The Journal of Finance* 72, 1611–1644.

Novy-Marx, Robert, 2018, Betting against betting against beta, *working paper* .

Parker, Jonathan A., and Christian Julliard, 2005, Consumption risk and the cross section of expected returns, *Journal of Political Economy* 113, 185–222.

Riding, Siobhan, and Emma Agyemang, 2019, How to recession-proof your investment portfolio, *Financial Times* August 23.

5. Tables and Figures

Table 1: Macro Hedged Portfolios and Post-Formation Betas. This table reports the portfolio exposure to all 8 macro series used in the hedge portfolio construction described in Section 1.1. To compute the expose, we regress the portfolio return on the macro factor considered, i.e. one full sample regression for each column. The macro factors are standardized so that exposures represent the annualized return response to a one standard deviation change in the macro variable. We compute exposures for three different portfolios. First, we report the exposure of the market portfolio in rows 1 and 2—these are the pre-hedge exposures. Second, we report the exposure of the zero-cost hedge portfolio in rows 3 and 4—these are the post-formation betas. Finally, we report the exposure of a portfolio long on the market and long-short on the zero-cost hedge portfolio ("Market Plus Hedge") in rows 5 and 6. See Section 1.1 for details.

	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)
Market Exposure	8.90	19.35	14.42	6.01	12.25	13.72	17.44	1.60
t-stat.	4.64	10.49	7.63	2.72	5.74	6.46	9.37	0.87
Hedge Portoflio Exposure	−5.93	−11.07	−7.85	−7.98	−15.81	−9.27	−11.47	−1.50
t-stat.	−3.16	−5.18	−3.77	−3.37	−5.46	−3.31	−4.58	−1.08
Market+Hedge Exposure	−3.28	−1.93	1.81	−3.69	−0.54	5.54	−3.86	−0.39
t-stat.	−1.36	−0.86	0.91	−1.56	−0.20	2.03	−1.49	−0.20

Table 2: Macro Hedged Portfolios and Exposure to Business Cycles. This table reports the exposure of a portfolio long on the market and long-short on the zero-cost hedge portfolio ("Market Plus Hedge") to different macroeconomic variables. Each column represents a different macro-hedge portfolio. Rows report exposure and *t*-statistic to different macroeconomic variables: NBER recessions, 1-quarter and 1-year aggregate consumption growth,1-quarter and 1-year GDP growth, 1-year aggregate dividend growth, 1-quarter and 1-year aggregate profits growth, Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017). All variables except the recession dummy are standardized to have unit standard deviation and returns are annualized. See Section 1.1 for details.

	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	−29.58	−21.05	−16.86	−15.54	−11.79	−15.10	−20.30	−11.75	−23.51
t-stat.	−5.97	−3.88	−3.39	−3.27	−1.70	−2.05	−2.70	−2.39	−3.70
1-quarter Δc	3.94	3.91	1.24	−0.33	−2.06	−3.82	−3.34	−1.51	0.20
t-stat.	2.05	1.67	0.60	−0.17	−0.61	−1.14	−0.96	−0.77	0.07
1-year Δc	8.30	8.60	5.57	4.49	4.20	1.81	2.96	3.96	5.25
t-stat.	4.09	3.20	2.12	2.09	1.73	0.50	0.95	2.00	2.24
1-quarter Δgdp	3.32	1.62	−0.86	−0.80	1.62	2.33	2.20	−1.98	1.68
t-stat.	1.73	0.69	−0.41	−0.42	0.53	0.75	0.69	−1.01	0.63
1-year Δgdp	10.39	7.47	4.68	5.89	5.08	4.30	7.61	4.17	7.93
t-stat.	5.45	2.61	1.82	2.88	1.70	1.33	2.33	2.04	3.00
1-year ΔDiv	12.13	9.12	6.50	6.58	4.93	1.21	4.66	6.34	6.01
t-stat.	7.22	4.10	2.96	3.20	1.72	0.41	1.53	3.05	2.70
1-quarter $\Delta Profit$	2.21	−2.44	−3.57	−0.89	−3.45	−4.50	−1.99	−3.80	−2.32
t-stat.	1.14	−1.03	−1.72	−0.46	−1.47	−1.94	−0.82	−1.94	−0.99
1-year $\Delta Profit$	5.19	−0.97	−0.92	2.64	−5.28	−4.52	0.74	−0.76	2.08
t-stat.	2.57	−0.37	−0.34	1.31	−2.11	−1.66	0.28	−0.43	0.84
1-year Δc_{pj}	8.04	2.13	−1.77	−2.39	4.50	1.77	0.12	−1.31	0.77
t-stat.	3.89	0.58	−0.51	−0.73	0.84	0.33	0.02	−0.40	0.21
1-year Δc_{q4}	5.55	4.98	2.45	1.45	2.56	3.06	1.58	2.37	4.11
t-stat.	2.56	1.86	0.97	0.60	0.69	0.83	0.39	0.98	1.77
1-year Δc_{unfil}	4.69	3.74	1.72	−0.07	0.43	2.05	−1.38	1.21	6.31
t-stat.	2.15	1.14	0.56	−0.02	0.07	0.35	−0.22	0.41	1.71

Table 3: Macro Hedged Portfolios, Average Returns, and Sharpe Ratios. Panel A reports several performance statistics of different hedge portfolios (Columns 2-9) described in Section 1.1. We report the annualized average return, volatility and Sharpe ratios. Panel B reports the same performance statistics for the market portfolio (Column 1) and for a portfolio long on the market and long-short on the zero-cost hedge portfolio ("Market Plus Hedge"). See Section 1.1 for details.

	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)
Panel A: hedge portfolio									
Avg. Return	–	−0.83	−1.33	−1.67	1.37	0.27	−0.18	0.28	−0.77
t-stat.	–	−0.55	−0.78	−0.95	0.62	0.10	−0.07	0.17	−0.52
Volatility	–	13.57	15.35	15.89	14.21	17.00	15.90	15.40	10.90
Sharpe ratio	–	−0.06	−0.09	−0.11	0.10	0.02	−0.01	0.02	−0.07
Panel B: market plus hedge portfolio									
Avg. Return	7.89	6.89	6.39	5.94	9.04	7.99	7.56	8.01	5.43
t-stat.	4.06	3.57	3.61	3.51	4.09	3.38	3.11	4.59	2.54
Volatility	18.54	17.39	15.92	15.18	14.08	15.04	15.37	15.72	15.76
Sharpe ratio	0.43	0.40	0.40	0.39	0.64	0.53	0.49	0.51	0.34

Table 4: Price of Risk Estimates of hedging factors. 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	7.64	6.97	5.73	8.55	8.45	7.56	8.31	6.23
t-stat.	4.56	4.04	2.89	4.41	4.01	2.97	5.54	3.13
λ_1	0.00	0.00	0.01	-0.01	-0.00	0.00	-0.01	0.06
t-stat.	0.58	0.67	0.94	-0.70	-0.28	0.17	-0.23	0.52
Adj. R^2	0.11	0.58	0.79	0.42	0.07	-0.07	-0.07	0.31
$\lambda_0/E[R]$	0.93	0.85	0.71	1.11	1.08	0.94	1.04	0.96

Table 5: Price of Risk Estimates of Leading Macro Factor Models. 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)
$\lambda_{0,pj}$	3.69	7.31	7.34	7.46	8.60	8.73	9.01	8.74	6.15
s.e.	2.86	2.27	2.07	1.97	3.60	2.36	2.69	1.80	2.44
$\lambda_{1,pj}$	3.31	1.54	1.49	1.24	−0.22	−0.30	−0.33	−0.16	0.89
s.e.	1.70	1.76	2.10	1.52	2.12	1.38	1.17	1.49	1.68
R^2	0.31	0.28	0.77	0.64	−0.12	−0.10	−0.07	−0.11	0.31
$\lambda_{0,q4}$	3.07	7.23	8.70	8.70	10.56	8.55	8.81	10.28	5.52
s.e.	4.47	2.32	3.50	2.50	3.22	2.79	2.86	2.51	3.08
$\lambda_{1,q4}$	1.75	0.38	−0.01	0.00	−0.75	−0.02	−0.03	−0.42	0.39
s.e.	0.77	0.45	0.98	0.57	0.67	0.47	0.58	0.61	0.83
R^2	0.60	0.08	−0.12	−0.12	0.11	−0.12	−0.12	0.13	0.12
$\lambda_{0,unfil}$	5.86	8.37	7.51	7.50	9.74	8.57	8.82	9.19	6.40
s.e.	3.00	2.14	2.21	2.09	3.35	2.76	2.65	1.91	2.89
$\lambda_{1,unfil}$	3.57	0.45	1.51	1.28	−1.85	−0.13	−0.14	−0.69	0.32
s.e.	1.95	1.22	2.67	1.74	1.22	0.90	0.93	1.68	1.37
R^2	0.25	−0.09	0.11	0.29	0.32	−0.12	−0.11	0.03	−0.10

Table 6: An Upper bound On the Pricing Implications of Recession Risk. In this Table we use our hedge portfolio approach to place an upper bound on the pricing implications of economic recessions. Specifically we use our macro hedge portfolio to eliminate all recession risk of a reference portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. We use as reference portfolios the market, the mve combination of the Fama-French 3 factor model, the mve combination of the Carhart model that adds momentum to the FF3, the mve combination of the Fama-French 5 factor model, and finally the mve combination of the factor model that adds momentum to the FF5. We take these reference portfolios as proxies for the tangency portfolio and apply the decomposition presented in Section 2.5. We report the Sharpe ratio of the original portfolio, the recession hedged version, the upper bound on the sdf variance due to recession risk, and the upper bound on the Sharpe ratio due to recession risk.

	Market	**FF3**	**Carhart**	**FF5**	**FF5+UMD**
Sharpe Ratio portfolio	0.43	0.52	0.98	1.10	1.26
Sharpe ratio recession hedged	0.36	0.61	0.84	1.18	1.26
Recession upper bound share	0.54	0.33	0.29	0.02	0.03
Recession upper bound Sharpe ratio	0.39	0.42	0.53	0.15	0.23

Table 7: Mean variance and Sharpe ratio of minimum variance portfolio. We form minimum variable portfolios and compute the mean, variance, and Sharpe ratio. 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	8.45	10.19	0.83
Car	8.14	9.70	0.84
FF5	8.07	9.73	0.83
FF5+ind	7.74	9.47	0.82

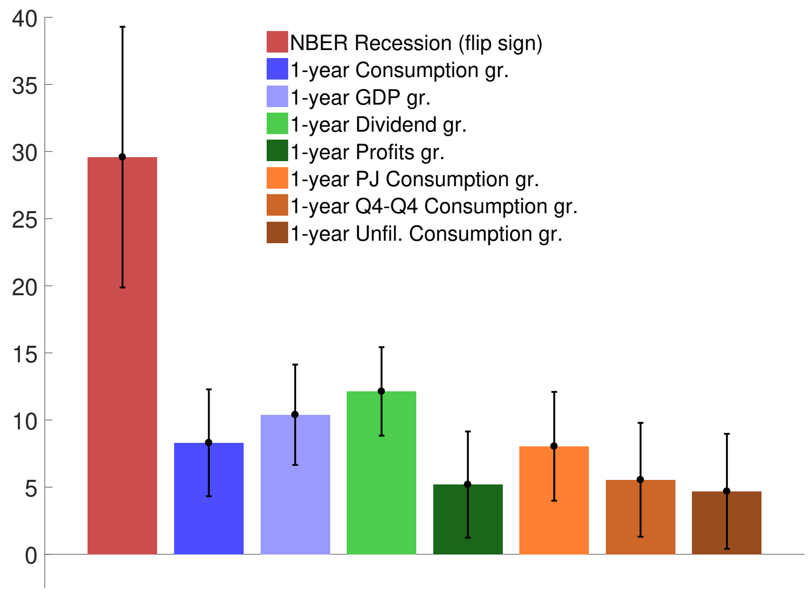
Table 8: Alphas of minimum variance portfolio. We form minimum variable portfolios as described in Table 7 and report their alpha with respect to different risk models (different columns).

	CAPM	3FF	3FF+MOM	5FF	5FF+MOM	5FF+MOM+BAB
Mkt Alpha	6.58	6.59	6.23	3.98	4.17	2.71
t-stat.	6.77	6.77	6.23	3.11	3.21	2.29
Info. ratio	0.72	0.72	0.68	0.44	0.46	0.33
Car Alpha	6.38	6.43	6.07	4.37	4.55	3.29
t-stat.	6.88	6.92	6.36	3.50	3.60	2.79
Info. ratio	0.73	0.73	0.69	0.50	0.52	0.41
FF5 Alpha	6.37	6.47	6.00	4.49	4.68	3.39
t-stat.	6.79	6.89	6.23	3.56	3.66	2.85
Info. ratio	0.72	0.73	0.68	0.51	0.53	0.41
FF5+ind Alpha	6.10	6.19	5.77	4.29	4.51	3.28
t-stat.	6.67	6.77	6.15	3.45	3.58	2.78
Info. ratio	0.71	0.72	0.67	0.49	0.52	0.40

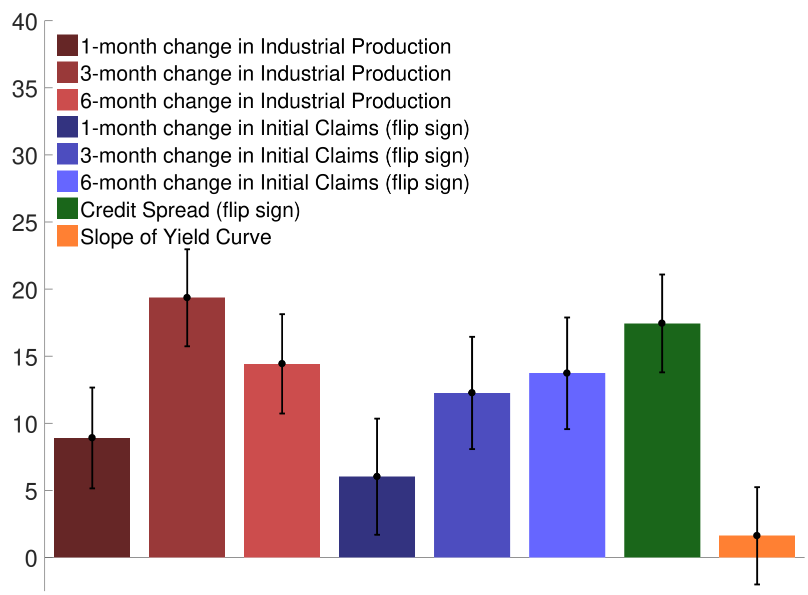
Table 9: Alphas of minimum variance portfolio (part 2). As in Table 8 above we form minimum variable portfolios as described in Table 7 and report their alpha with respect to different risk models (different columns). But now use the equal-weighted market portfolio instead of the value-weighted market portfolio in the different risk models.

	CAPM	3FF	3FF+MOM	5FF	5FF+MOM	5FF+MOM+BAB
Mkt Alpha	6.55	6.74	6.12	4.02	3.88	2.75
t-stat.	6.77	6.99	6.18	3.22	3.04	2.34
Info. ratio	0.72	0.74	0.67	0.46	0.44	0.34
Car Alpha	6.39	6.58	5.98	4.39	4.27	3.30
t-stat.	6.89	7.13	6.32	3.59	3.43	2.81
Info. ratio	0.73	0.76	0.69	0.51	0.50	0.41
FF5 Alpha	6.37	6.61	5.90	4.51	4.39	3.40
t-stat.	6.80	7.10	6.18	3.65	3.49	2.87
Info. ratio	0.72	0.75	0.67	0.52	0.50	0.42
FF5+ind Alpha	6.09	6.33	5.70	4.30	4.23	3.29
t-stat.	6.67	6.97	6.11	3.53	3.41	2.80
Info. ratio	0.71	0.74	0.67	0.50	0.49	0.41

Figure 1: Market Exposure to Macro Factors. This figure plots the market portfolio exposure to different macro economic indicators. In Panel A, we report exposure to NBER recession, as well as annual growth rates of consumption, GDP, dividend, profits, and Parker-Julliard consumption factor. In Panel B, we report exposures to all 8 macro series used in the hedge portfolio construction described in Section 1.1. To compute the exposures, we regress the market portfolio return on the macro factor considered, i.e. one full sample regression for each column. In Panel B, the macro indicators are standardized to have mean zero and variance one and returns are annualized. See Section 1.1 for details.



Panel A



Panel B

Figure 2: Exposures of Macro Hedge Portfolio to Macro Variables. We plot exposures (and a 95% confidence interval) to several macro variables for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$. See text for additional details.

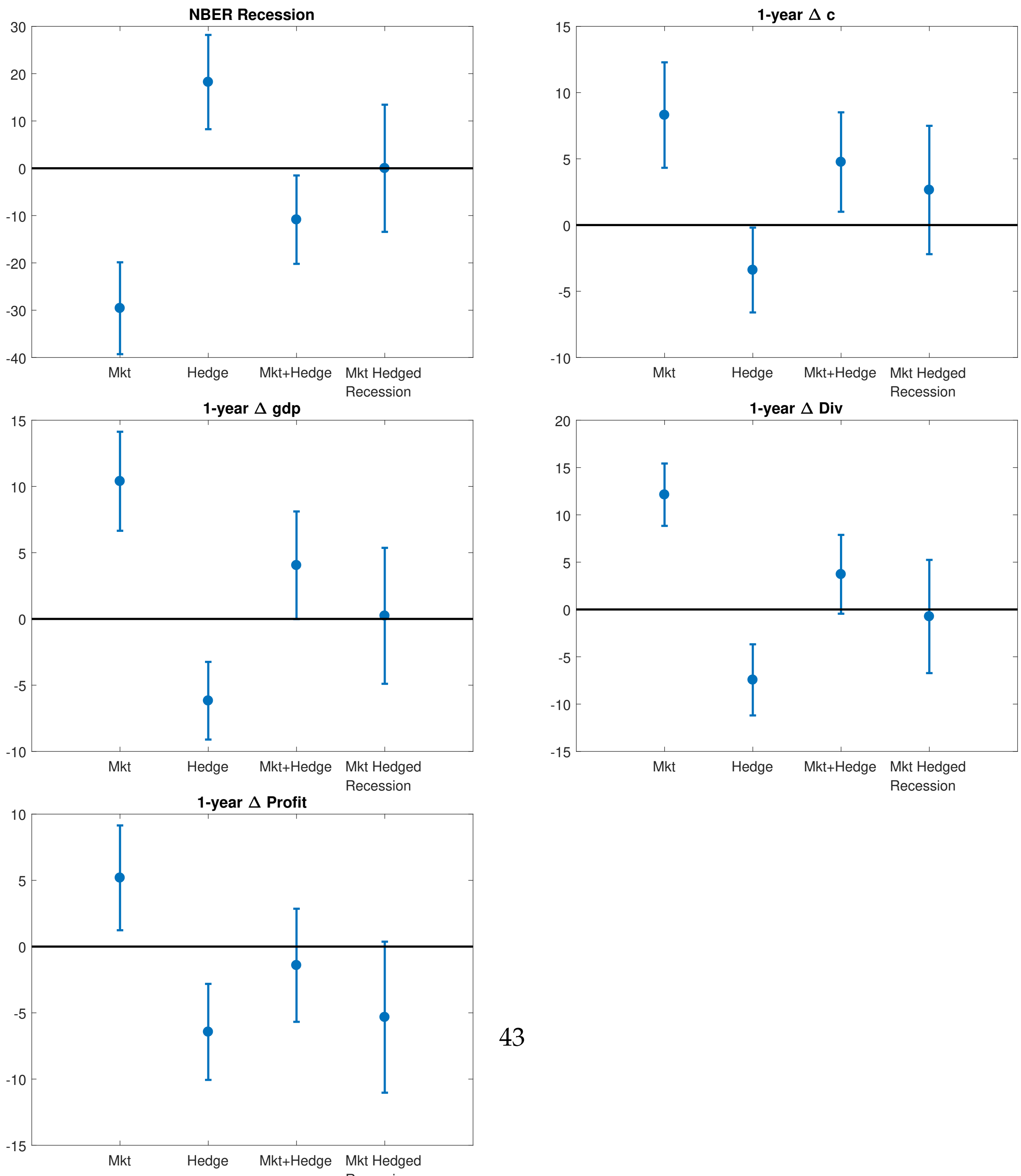


Figure 3: Exposures of Macro Hedge Portfolio to Consumption-Based Factors.We plot exposures (and a 95% confidence interval) to several consumption factors for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$. See text for additional details. We plot exposure of our macro hedge to various business cycle and macroeconomic factors. The Consumption factors are Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017).

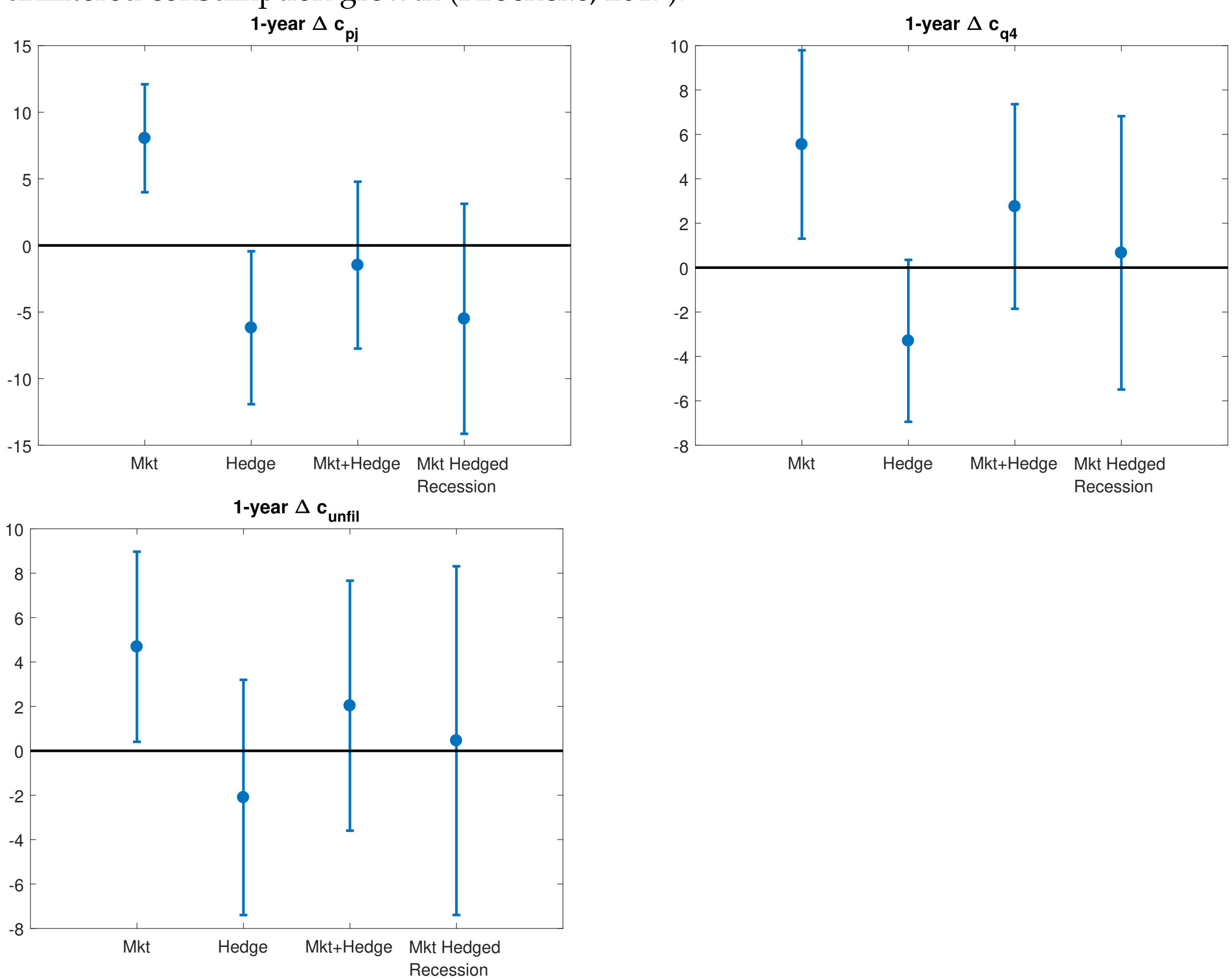


Figure 4: Cumulative Return to Macro Hedges Around Selected Recessions. We plot cumulative returns the market portfolio around selected recessions as well as the market portfolio plus our macroeconomic hedge portfolio based on our combined-macro factor to give a sense of how this portfolio helps lessen exposure to recessions. We consider the most recent five recessions. For comparison, and to show this is not just about hedging general market downturns, we also show the 1987 crash which did not involve a major recession or macroeconomic decline but did result in a large market crash.

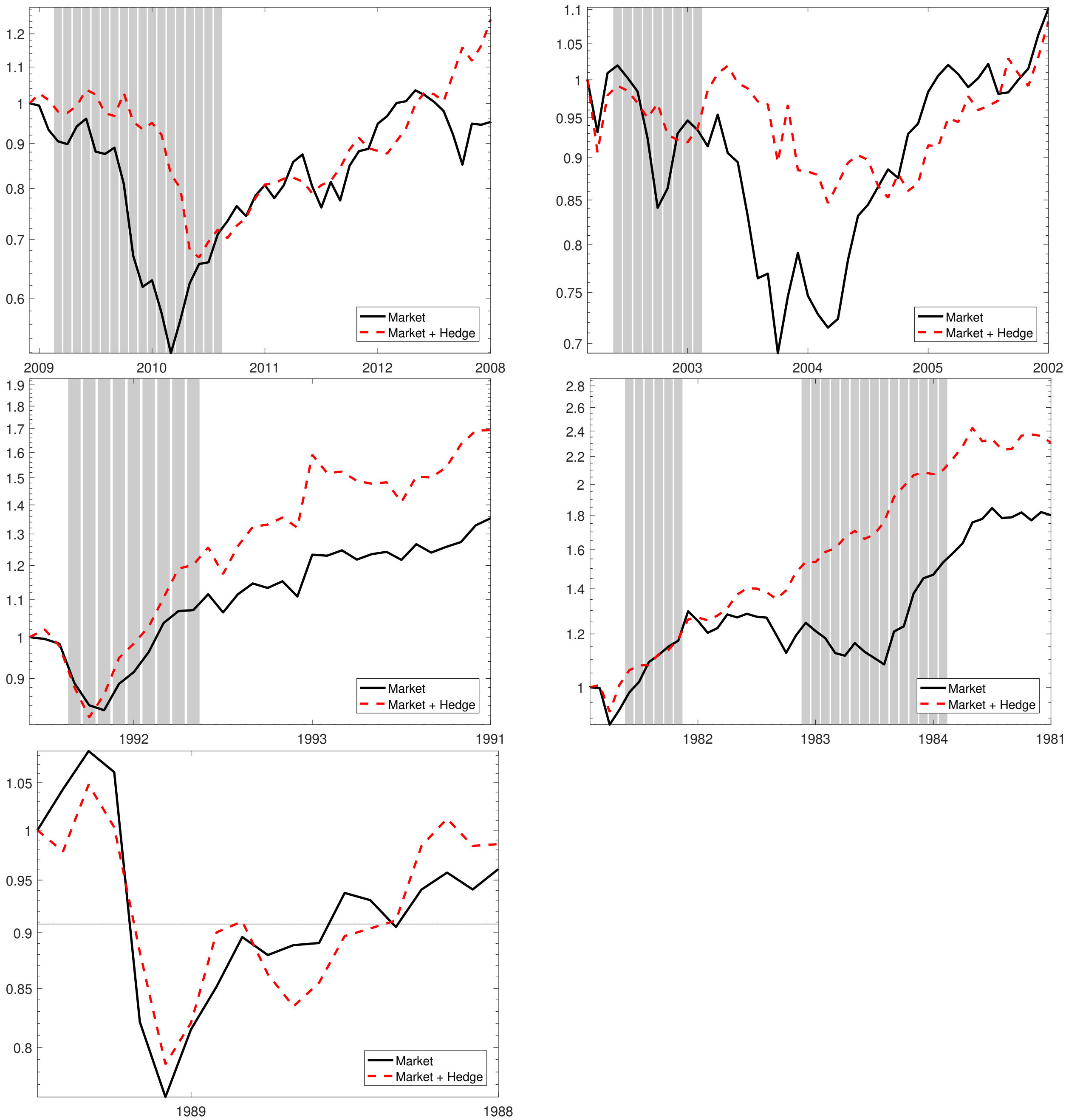


Figure 5: Risk Premium of Macro Hedge Portfolios. We plot the annualized average return and a 95% confidence interval for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$. See text for additional details.

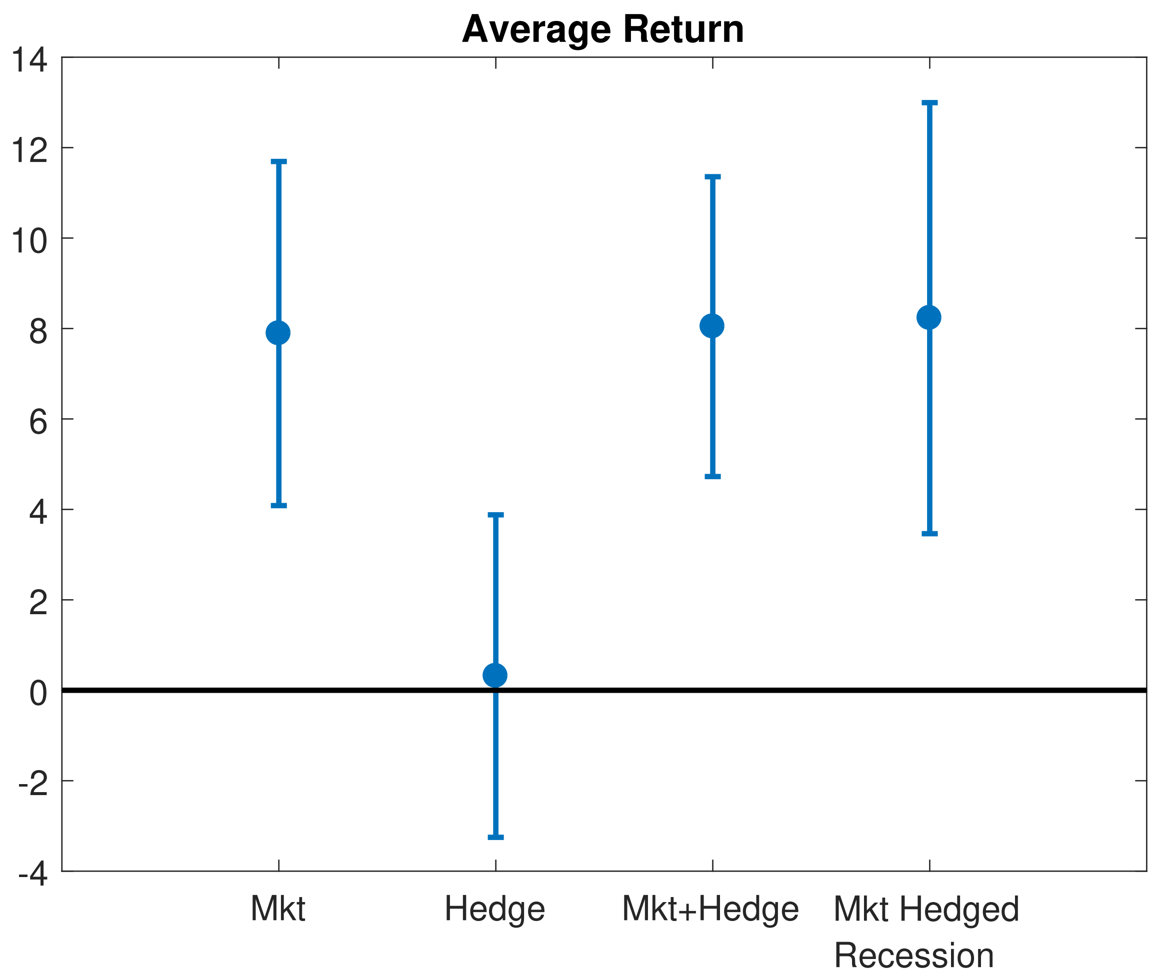


Figure 6: Price of Risk Estimates of Leading Macro Factor Models. We plot prices of risk estimated from FF25 vs our ten macro hedge portfolios (formed by sorting on betas to our equal weight macro risk series, see text for details). We estimate this price of risk for Parker and Julliard (future consumption over three years, labeled "pj"), Jagannathan and Wang (fourth quarter to fourth quarter consumption, labeled "q4"), and Kroencke (unfiltered NIPA consumption, labeled "unfil"). Confidence bands are shown using Shanken standard errors.

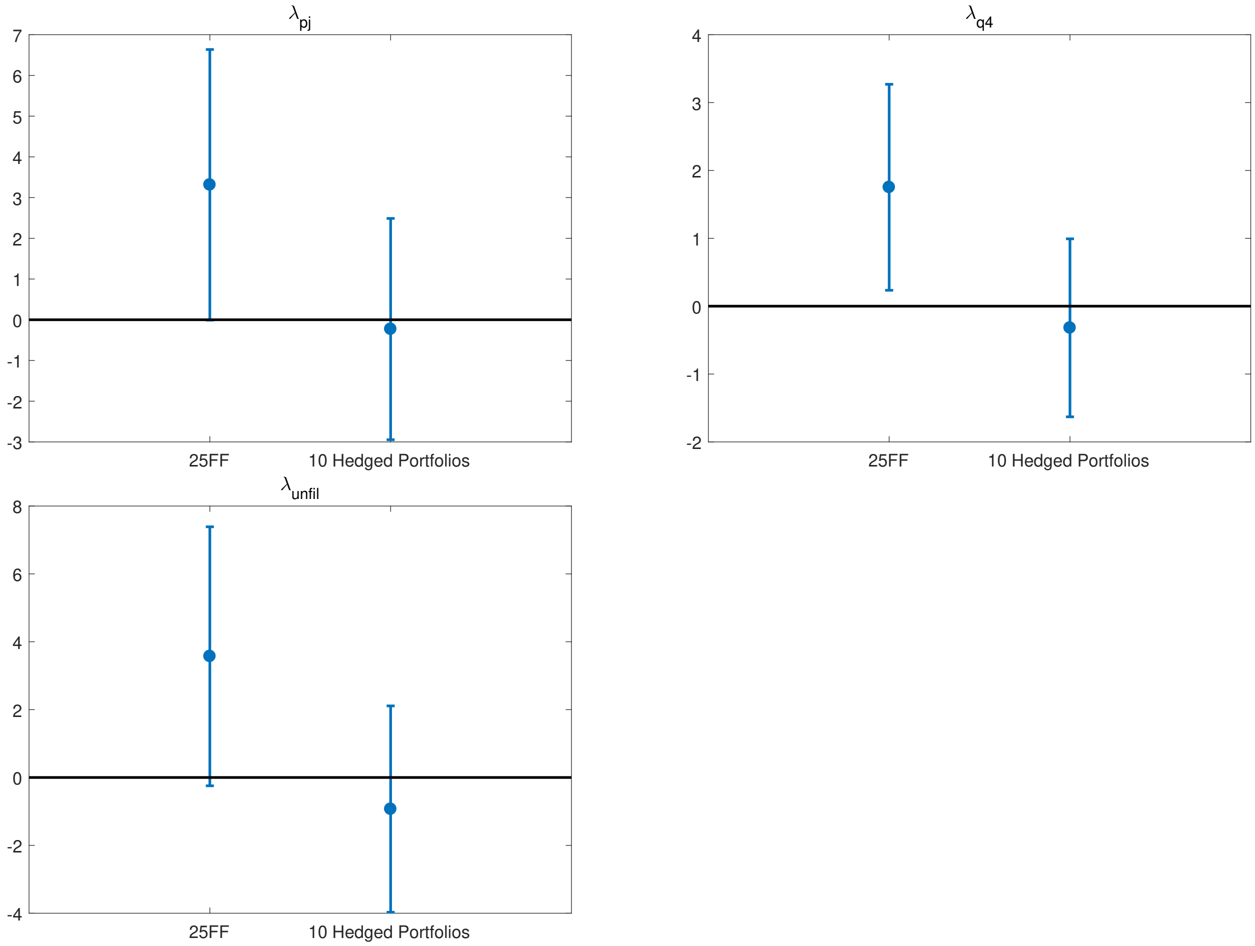


Figure 7: Alphas of beta sorted portfolios. We plot alphas on each individual factor against post-formation betas formed in univariate regressions on each factor. The y-axis is in annualized return units (e.g., 10 means 10% per year). We form 10 beta sorted portfolios on each factor individually then 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).

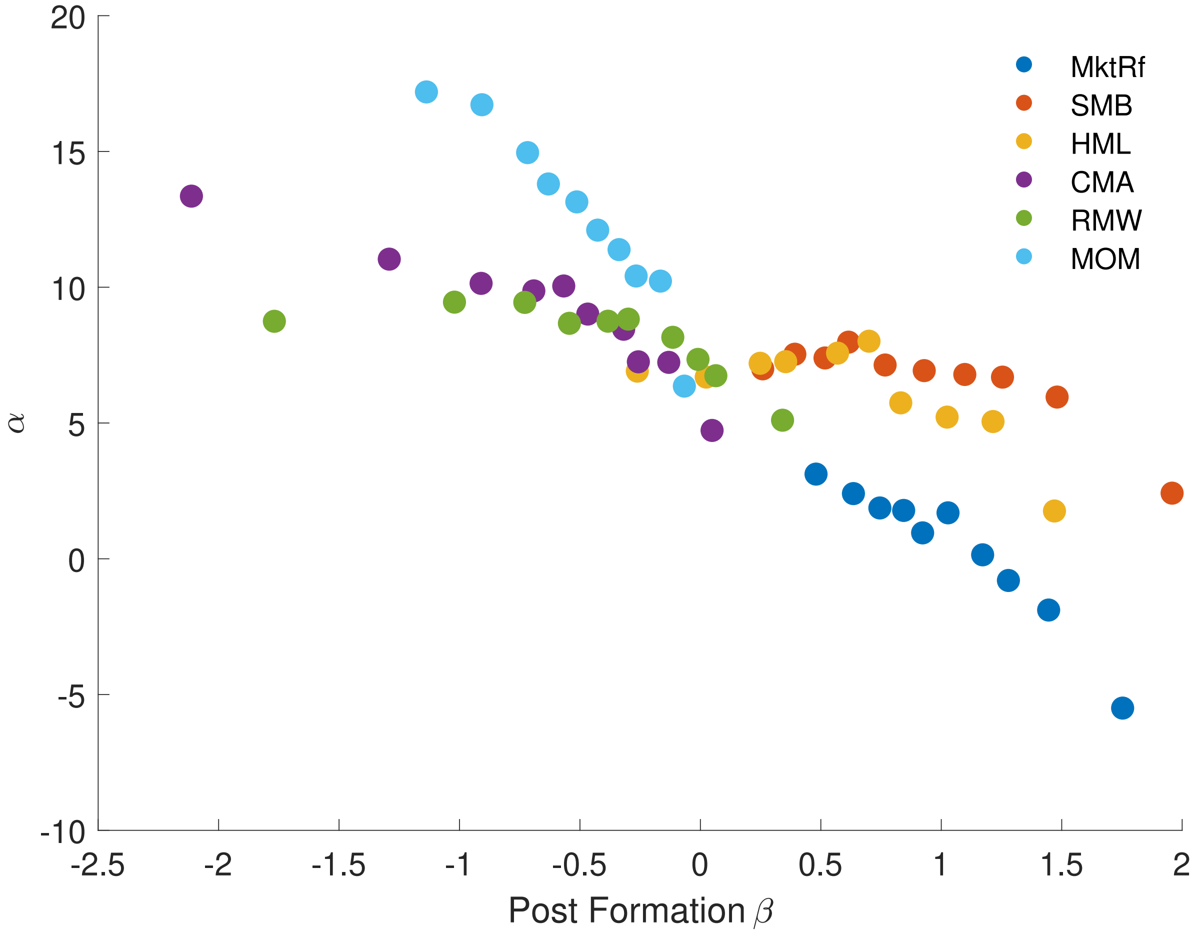
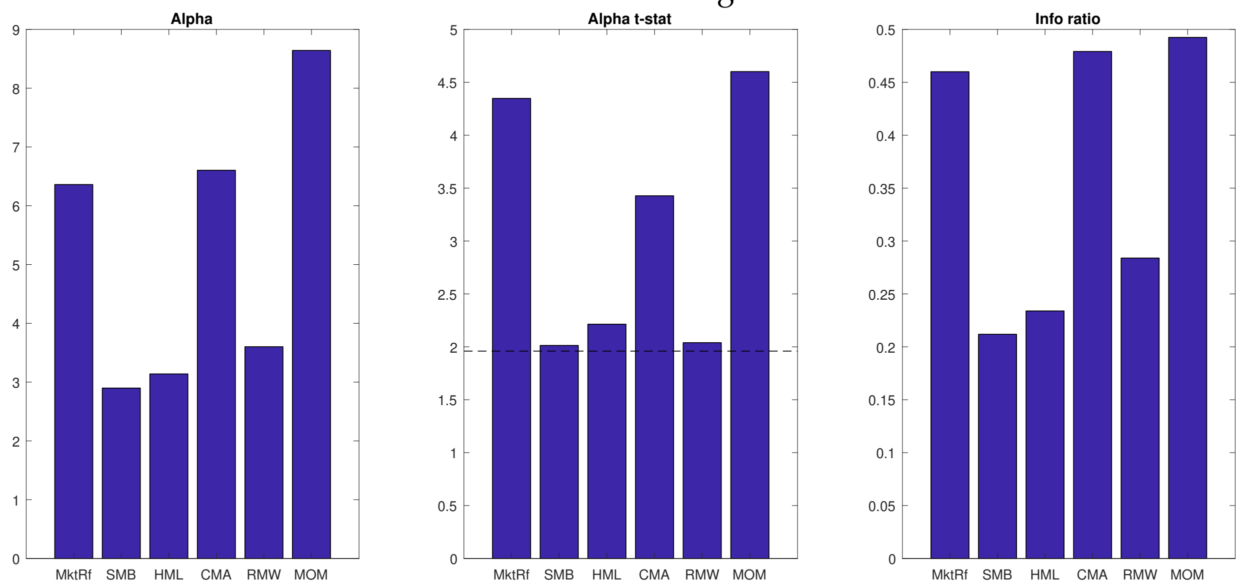


Figure 8: Beta sorted portfolios. We plot alphas on beta sorted portfolios by factor. We sort stocks by their beta with respect to individual factors and then form a beta factor using the low minus high beta portfolio based on pre-ranking beta quintiles. The first panel shows the results controlling 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

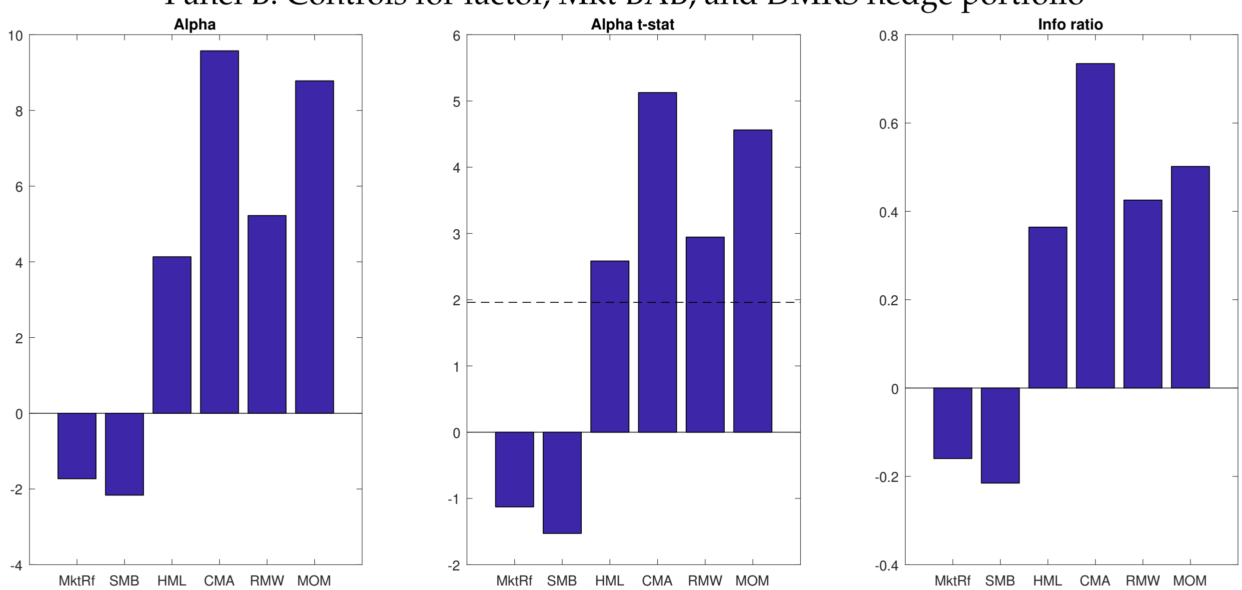
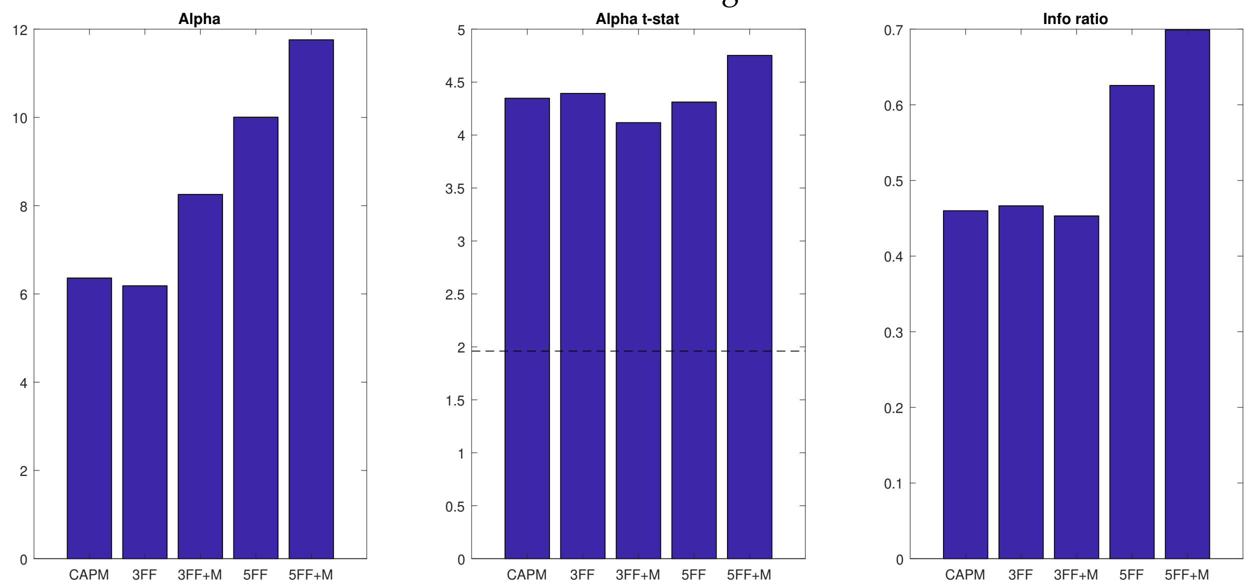


Figure 9: Multi-factor beta sorted portfolios (MVE). We plot alphas on beta sorted portfolios with respect to mutifactor benchmark r^*. We repeat the exercise from the last figure, but instead of using single factors to beta sort, we use ex-post MVE combinations of factors (e.g., $b'F$ where F is a set of factors and b is chosen to maximize full sample Sharpe ratios).

Panel A: Controls for original factor



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

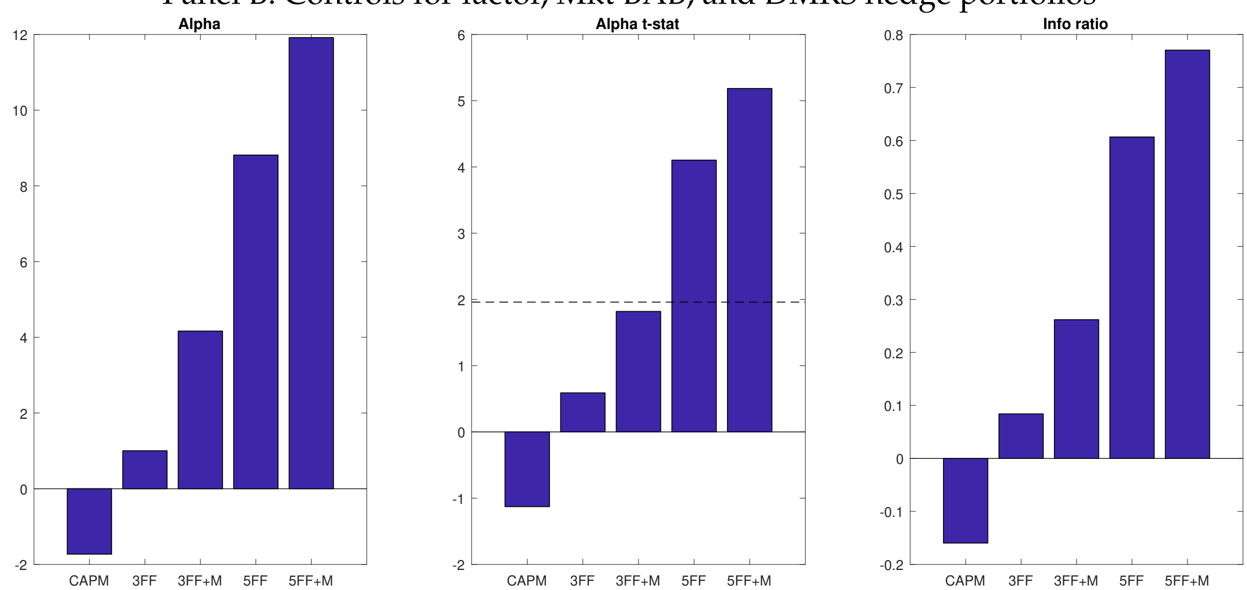
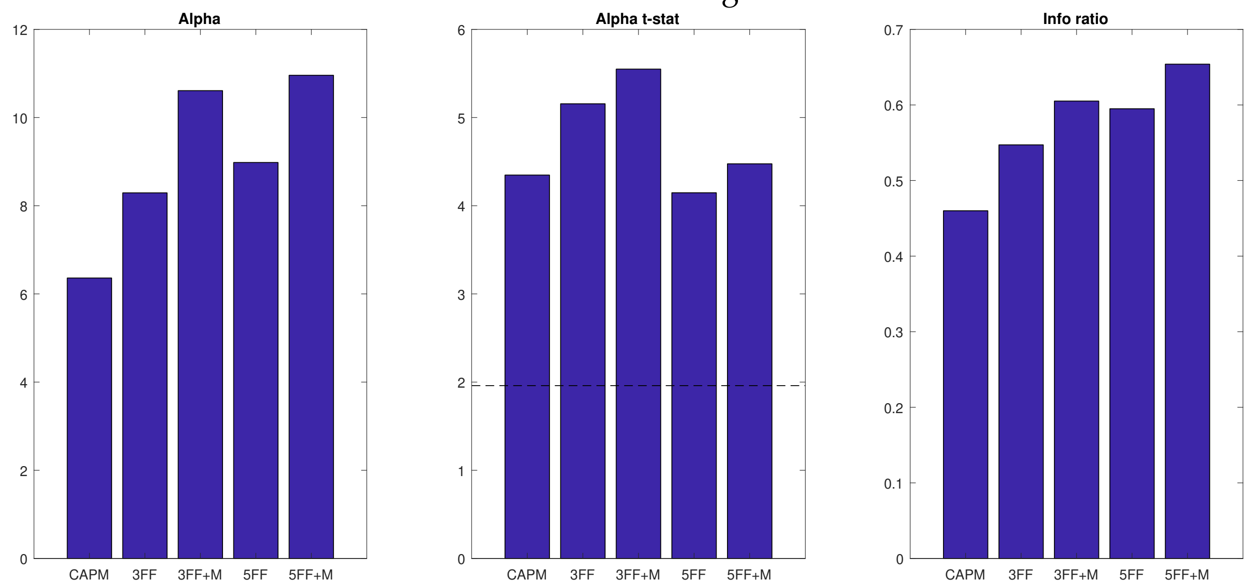
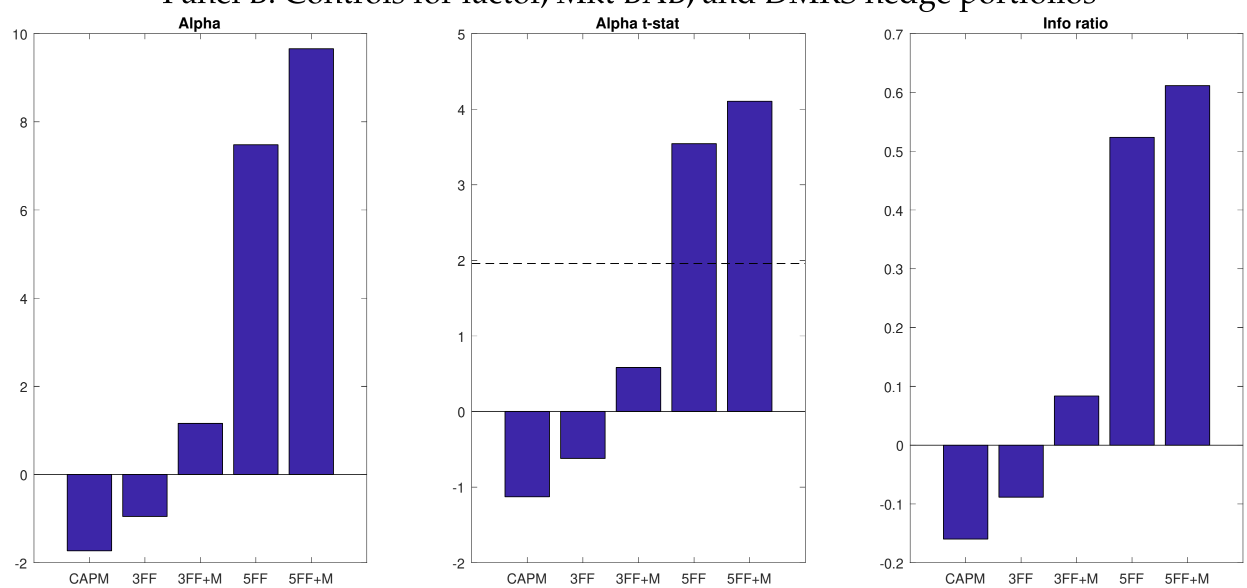


Figure 10: Multi-factor beta sorted portfolios (EW). We plot alphas on beta sorted portfolios with respect to mutifactor benchmark r^*. We repeat the exercise from the last figure, but instead of using in-sample MVE portfolios to beta sort, we use a equally weight average (EW) of factors.

Panel A: Controls for original factor



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



Appendix for
"Hedging Risk Factors"

. Additional Tables

A Additional analysis

This appendix runs a number of robustness checks and presents many additional results. The appendix does three things. First, it considers other macro factors as priced sources of risk including luxury consumption, NVIX, and the TED spread and shows similar results to what we document in the main text when considering these factors as well (Tables A1-A3, Figures A9-A12). Second, it considers intermediary-based factors for the cross-section (Figures A13-A15). Third, it examines our macro hedged portfolios when we control for market betas and also double sort based on market betas and our macro factor betas to assess the overlap between market betas and macro betas (Figures A1-A8). We briefly describe these in more detail.

First we consider other macro factors to evaluate our hedge portfolios including luxury consumption goods (Ait-Sahalia, Parker, and Yogo, 2004) where we use the boats index. We next include NVIX (Manela and Moreira, 2017) and the uncertainty index (Baker, Bloom, and Davis, 2016) as measures of economic uncertainty, and the TED spread as a measure of financial market stress (Frazzini and Pedersen, 2014). The TED spread is of particular interest as Frazzini and Pedersen (2014) argue that exposure to the TED spreads helps explain the betting against beta factor using market betas. We find TED itself can be hedged at very low cost. The results are presented in Tables A1-A3 and Figures A9-A12. These factors have also been argued to explain the cross-section of returns or be priced factors and we give evidence they can be hedged as well at low costs. We find that our macro sorted portfolios do help to hedge against these factors as we found for the factors considered in the main text.

Tables A4-A5 evaluate quarterly series for consumption and GDP as our macro variables used in our sorting procedure. That is, we construct betas using quarterly returns on these quarterly series as we did with the monthly macro proxies in the main text. We find similar results in most cases, though there is some additional noise using quarterly data (as expected). Thus, the monthly macro series we use in the main text mainly serve to proxy for other macro series but leverage higher frequency data to form better beta estimates.

Then we investigate intermediary factors including Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017). We run the same exercises as before but include these factors and estimate prices of risk, finding fairly similar results to what is reported in the main text. Figures A13-A15. We use both the capital factor from He et al. (2017) (listed as HKM1) and the traded return series which is a value-weighted excess return on primary dealers (listed as HKM2). In these cases we also find that sorting on HKM factor betas produces different prices of risk for both He et al. (2017) and Adrian et al. (2014) then using the Fama-French 25 portfolios.

We then return to our main macro variable analysis, hedging macroeconomic risk factors, but control for market betas in addition to our macro variable in the analysis in Figure A1-A8. We do this in two ways. First, we simply run multivariate regressions controlling for the market when we construct our macro hedge portfolios, and then we double sort portfolios based on both market and macro betas. In the main text our only goal is to provide good ex-post spread in macro betas, so we don't want to control for the market if it provides useful information on these betas. Still, for completeness, we want to evaluate whether all of this could be captured by market betas. We find qualitatively similar (though slightly weaker) results when we control for market betas in our portfolio sorts.

To better deal with this issue, we also double sort on market beta and macro betas then average across market beta quintiles in our macro beta sorts. We find weaker but qualitatively similar results, suggesting the market betas do pick up some of the macro risk we are interested in but that there is still a role for the macro factor in addition to market beta. In sum, the results suggest that market beta does overlap with our macro beta to some extent though there is also independent variation.

Table A.1: Macro Hedged Portfolios: Additional Portfolios. Here we construct macro-hedge portfolios based on the following additional factors:TED spread, Boats consumption, News implied volatility from (Manela and Moreira, 2017), and economic policy uncertainty from (Baker et al., 2016). Panel A reports several performance statistics of the market portfolio (Column 1) and different hedge portfolios (Columns 2-9) described in Section 1.1. We report the annualized average return, volatility and Sharpe ratios, and post-formation betas. First, we construct the hedge portfolio sorted on pre-formation betas. Once the portfolio is formed, we estimate post-formation betas from a full sample regression of the hedge portfolio on the original factor. In Panel B, we report these statistic for a portfolio long on the market and long-short on the zero-cost hedge portfolio ("Market Plus Hedge"). We also report the portfolio exposure before and after adding the hedge position. In Panel C, we report the annualized exposures of the Market Plus Hedge portfolio to different macroeconomic variables: NBER recessions, 1-quarter and 1-year aggregate consumption growth,1-quarter and 1-year GDP growth, 1-year aggregate dividend growth, 1-quarter and 1-year aggregate profits growth, Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017).

Panel A: Hedge Portfolios

	Mkt.	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)	(5)
Avg. Return	–	1.98	0.82	0.71	−0.35
t-stat.	–	0.71	0.45	0.50	−0.10
Volatility	–	13.03	12.66	11.44	17.33
Sharpe ratio	–	0.15	0.06	0.06	−0.02
Post-formation β	–	−8.70	−3.40	−5.01	−12.74
t-stat.	–	−3.02	−1.98	−3.60	−3.75

Panel B: Market Plus Hedge

	Mkt.	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)	(5)
Avg. Return	7.89	9.33	6.93	7.65	7.77
t-stat.	4.06	2.84	3.04	3.11	2.62
Volatility	18.54	15.24	15.86	19.63	14.05
Sharpe ratio	0.43	0.61	0.44	0.39	0.55
Post-hedge exposure	–	−3.55	2.89	3.72	0.03
t-stat.	–	−1.04	1.34	1.54	0.01
Pre-hedge exposure	–	11.31	5.26	10.93	13.29
t-stat.	–	4.27	2.68	5.33	5.17

Table A.1 (continued)

Panel B: Market Plus Hedge

	Mkt.	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)	(5)
Recession	−29.58	−29.22	−20.17	−20.60	−18.35
t-stat.	−5.97	−2.70	−3.11	−3.21	−1.83
1-quarter Δc	3.94	11.66	0.15	0.96	1.34
t-stat.	2.05	2.03	0.05	0.47	0.25
1-year Δc	8.30	8.37	3.57	5.44	5.83
t-stat.	4.09	3.19	0.99	2.60	1.81
1-quarter Δgdp	3.32	13.31	3.71	−0.56	8.56
t-stat.	1.73	2.55	1.31	−0.27	1.81
1-year Δgdp	10.39	10.31	6.43	5.70	7.67
t-stat.	5.45	3.83	1.68	2.77	1.77
1-year ΔDiv	12.13	4.95	3.53	6.64	−0.65
t-stat.	7.22	1.81	1.31	2.46	−0.19
1-quarter $\Delta Profit$	2.21	−1.13	−1.66	−2.81	−6.33
t-stat.	1.14	−0.41	−0.69	−1.34	−2.69
1-year $\Delta Profit$	5.19	−3.37	−0.78	4.77	−7.31
t-stat.	2.57	−1.14	−0.25	1.78	−2.33
1-year Δc_{pj}	8.04	7.47	0.66	1.97	9.55
t-stat.	3.89	1.36	0.14	0.49	1.60
1-year Δc_{q4}	5.55	8.77	4.27	4.48	7.31
t-stat.	2.56	2.51	1.42	1.80	1.70
1-year Δc_{unfil}	4.69	11.13	3.79	2.44	12.74
t-stat.	2.15	1.76	0.81	0.70	1.78

Table A.2: Asset Pricing Tests of Macro Beta Portfolios: Additional Portfolios. Here we construct macro-hedge portfolios based on the following additional factors:TED spread, Boats consumption, News implied volatility from (Manela and Moreira, 2017), and economic policy uncertainty from (Baker et al., 2016). 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		8.48	6.00	8.32	8.48
	t-stat.	2.89	2.84	3.05	3.45
λ_1		-0.05	0.01	-0.41	-0.00
	t-stat.	-0.83	0.17	-0.61	-0.07
Adj. R^2		0.32	-0.10	0.25	-0.12
$\lambda_0/E[R]$		1.13	0.95	1.17	1.03

Table A.3: Price of Risk Estimates of Leading Macro Factor Models : Additional Portfolios. Here we construct macro-hedge portfolios based on the following additional factors:TED spread, Boats consumption, News implied volatility from (Manela and Moreira, 2017), and economic policy uncertainty from (Baker et al., 2016). 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	Ted	Boats	Nvix	Uncertainty
	(1)	(2)	(3)	(4)	(5)
$\lambda_{0,pj}$	3.69	5.41	8.38	9.33	9.59
s.e.	2.86	4.84	2.73	2.74	5.55
$\lambda_{1,pj}$	3.31	1.49	−0.88	−1.53	−0.76
s.e.	1.70	1.35	1.34	1.60	1.44
R^2	0.31	0.14	0.12	0.35	−0.04
$\lambda_{0,q4}$	3.07	4.84	7.03	8.96	10.84
s.e.	4.47	6.39	3.52	2.68	6.28
$\lambda_{1,q4}$	1.75	0.68	0.06	−0.16	−0.61
s.e.	0.77	0.63	0.89	0.52	0.68
R^2	0.60	0.23	−0.12	−0.10	0.20
$\lambda_{0,unfil}$	5.86	5.08	7.84	8.96	11.36
s.e.	3.00	6.06	3.25	2.70	6.88
$\lambda_{1,unfil}$	3.57	1.10	−0.24	−1.31	−1.27
s.e.	1.95	1.02	1.58	1.22	1.32
R^2	0.25	0.18	−0.11	0.40	0.37

Table A.4: Macro Hedged Portfolios: quarterly series. Here we replicate our analysis of Section 1.1, in the main text, but now using quarterly data to estimate betas and form portfolios. Specifically, we estimate the betas using a rolling regression with a window of 20 quarters.

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.5: Asset Pricing Tests of Macro Beta Portfolios: quarterly series. Here we replicate our analysis of Table 4 in the main text, but now using quarterly data to estimate betas and form portfolios. Specifically, we estimate the betas using a rolling regression with a window of 20 quarters.

	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

Table A.6: Macro Hedged Portfolios: Alternative Beta Estimation. Here we estimate betas using a rolling window of seven years using only monthly data. Panel A reports several performance statistics of the market portfolio (Column 1) and different hedge portfolios (Columns 2-9) described in Section 1.1. We report the annualized average return, volatility and Sharpe ratios, and post-formation betas. First, we construct the hedge portfolio sorted on pre-formation betas. Once the portfolio is formed, we estimate post-formation betas from a full sample regression of the hedge portfolio on the original factor. In Panel B, we report these statistic for a portfolio long on the market and long-short on the zero-cost hedge portfolio ("Market Plus Hedge"). We also report the portfolio exposure before and after adding the hedge position. In Panel C, we report the annualized exposures of the Market Plus Hedge portfolio to different macroeconomic variables: NBER recessions, 1-quarter and 1-year aggregate consumption growth,1-quarter and 1-year GDP growth, 1-year aggregate dividend growth, 1-quarter and 1-year aggregate profits growth, Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017). See Section 1.1 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	–	−0.67	−1.35	−1.11	1.86	1.68	1.74	0.92	−0.79
t-stat.	–	−0.43	−0.79	−0.64	0.91	0.65	0.73	0.54	−0.56
Volatility	–	14.23	15.75	15.84	13.50	16.92	15.60	15.65	10.76
Sharpe ratio	–	−0.05	−0.09	−0.07	0.14	0.10	0.11	0.06	−0.07
Post-formation β	–	−7.51	−13.91	−10.26	−5.58	−14.14	−8.86	−13.38	−2.92
t-stat.	–	−4.28	−6.98	−5.24	−2.62	−5.47	−3.58	−5.67	−2.14

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	7.89	7.55	6.87	7.10	9.14	9.17	9.64	9.15	5.57
t-stat.	4.06	3.88	3.85	4.04	4.01	3.98	4.07	5.41	2.51
Volatility	18.54	17.86	16.36	16.06	15.05	15.15	15.55	15.51	16.81
Sharpe ratio	0.43	0.42	0.42	0.44	0.61	0.61	0.62	0.59	0.33
Post-hedge exposure	–	−5.06	−4.10	0.24	−0.92	−0.66	4.65	−4.94	−1.93
t-stat.	–	−2.28	−1.94	0.12	−0.38	−0.28	1.87	−2.09	−0.90
Pre-hedge exposure	–	8.90	19.35	14.42	6.01	12.25	13.72	17.44	1.60
t-stat.	–	4.64	10.49	7.63	2.72	5.74	6.46	9.37	0.87

Table A.6 (continued)

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	−29.58	−22.81	−16.90	−15.04	−18.31	−10.88	−14.98	−11.04	−23.85
t-stat.	−5.97	−4.11	−3.31	−3.00	−2.68	−1.55	−2.04	−2.28	−3.63
1-quarter Δc	3.94	4.17	1.18	−1.37	0.41	−2.11	−5.32	−0.19	0.79
t-stat.	2.05	1.75	0.57	−0.64	0.13	−0.68	−1.68	−0.10	0.26
1-year Δc	8.30	8.48	5.37	3.54	6.02	3.12	0.19	4.81	6.41
t-stat.	4.09	3.47	2.35	1.65	2.17	1.14	0.06	2.49	2.66
1-quarter Δgdp	3.32	2.00	−1.47	−1.71	3.81	1.06	−2.29	−1.87	1.58
t-stat.	1.73	0.83	−0.71	−0.80	1.29	0.37	−0.77	−0.98	0.56
1-year Δgdp	10.39	8.39	4.84	5.67	7.49	3.56	3.31	4.44	9.65
t-stat.	5.45	3.22	2.22	2.65	2.03	1.30	1.04	2.31	3.37
1-year ΔDiv	12.13	8.30	5.32	6.84	6.16	0.53	4.96	5.56	8.90
t-stat.	7.22	3.95	2.76	3.29	2.47	0.22	1.83	2.97	3.62
1-quarter $\Delta Profit$	2.21	−2.21	−4.19	−0.17	−2.60	−5.12	−0.01	−2.83	−0.69
t-stat.	1.14	−0.91	−2.02	−0.08	−1.12	−2.32	−0.01	−1.48	−0.27
1-year $\Delta Profit$	5.19	−0.03	−0.89	2.52	−3.04	−3.71	2.32	−0.32	3.08
t-stat.	2.57	−0.01	−0.32	1.05	−1.07	−1.44	1.02	−0.16	1.19
1-year Δc_{pj}	8.04	2.59	0.69	−1.59	4.43	3.88	−1.59	0.17	0.92
t-stat.	3.89	0.83	0.25	−0.53	0.96	0.94	−0.32	0.06	0.22
1-year Δc_{q4}	5.55	5.48	3.25	1.07	3.24	4.61	0.57	3.55	4.86
t-stat.	2.56	2.04	1.37	0.41	1.01	1.64	0.16	1.55	1.83
1-year Δc_{unfil}	4.69	3.14	1.76	−0.38	2.64	5.21	−2.31	0.97	4.81
t-stat.	2.15	1.11	0.70	−0.14	0.52	1.16	−0.43	0.40	1.12

Table A.7: Asset Pricing Tests of Macro Beta Portfolios: Alternative Beta Estimation. Here we estimate betas using a rolling window of seven years using only monthly data. 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	8.02	7.78	7.16	8.22	8.01	8.65	9.15	6.54
t-stat.	4.67	4.85	4.05	3.99	3.66	3.35	6.31	3.31
λ_1	0.00	0.00	0.01	−0.01	−0.00	−0.00	−0.01	0.06
t-stat.	0.83	0.66	0.82	−0.40	−0.03	−0.09	−0.49	0.44
Adj. R^2	0.14	0.31	0.54	0.07	−0.12	−0.11	0.17	0.03
$\lambda_0/E[R]$	0.92	0.89	0.81	1.09	1.01	1.03	1.07	0.97

Table A.8: Price of Risk Estimates of Leading Macro Factor Models : Alternative Beta Estimation. Here we estimate betas using a rolling window of seven years using only monthly data. 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)
$\lambda_{0,pj}$	3.69	7.75	7.90	8.22	8.99	8.42	10.34	9.98	6.76
s.e.	2.86	2.43	2.18	1.98	4.19	2.69	2.64	1.84	2.42
$\lambda_{1,pj}$	3.31	1.71	1.58	1.21	0.29	1.20	−0.82	−0.65	0.53
s.e.	1.70	1.36	2.28	1.46	2.64	2.06	1.58	1.71	1.88
R^2	0.31	−0.03	0.13	0.37	−0.11	−0.03	0.13	−0.00	−0.07
$\lambda_{0,q4}$	3.07	10.44	9.36	9.17	9.23	8.06	11.11	10.09	7.85
s.e.	4.47	2.57	3.72	2.33	3.52	4.89	3.59	2.53	3.11
$\lambda_{1,q4}$	1.75	−0.41	−0.12	−0.04	0.00	0.50	−0.50	−0.36	−0.18
s.e.	0.77	0.48	1.11	0.53	0.61	0.99	1.02	0.74	0.88
R^2	0.60	−0.04	−0.10	−0.12	−0.12	−0.01	0.16	−0.04	−0.11
$\lambda_{0,unfil}$	5.86	11.32	10.18	8.33	9.49	9.51	10.45	10.83	6.42
s.e.	3.00	3.55	2.29	2.00	3.03	3.58	2.81	2.62	2.60
$\lambda_{1,unfil}$	3.57	−2.37	−0.97	1.38	−0.21	0.01	−0.80	−1.80	0.52
s.e.	1.95	1.97	1.28	1.80	1.03	1.36	1.40	3.81	1.30
R^2	0.25	0.06	−0.07	0.27	−0.11	−0.12	0.24	0.16	−0.08

Figure A.1: Risk Premium of Macro Hedge Portfolios: Controlling for Market Exposure in Pre-formation Beta Estimation. Here we control for the market portfolio when estimating pre-formation macro-factor betas. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. We plot the annualized average return and a 95% confidence interval for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$.

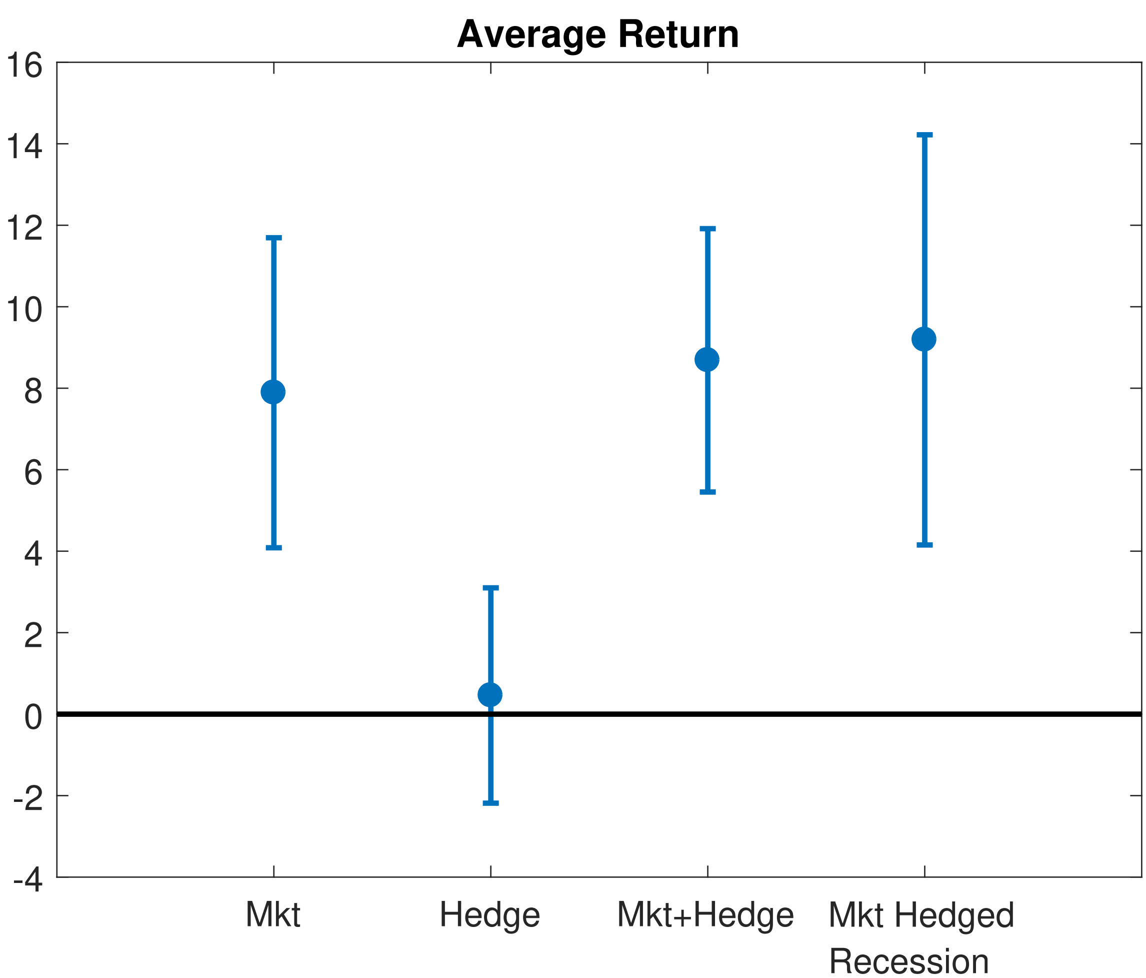


Figure A.2: Exposures of Macro Hedge Portfolio to Macro Variables: Controlling for Market Exposure in Pre-formation Beta Estimation. Here we control for the market portfolio when estimating pre-formation macro-factor betas. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. We plot exposures to various macroeconomic factors (and a 95% confidence interval) for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$.

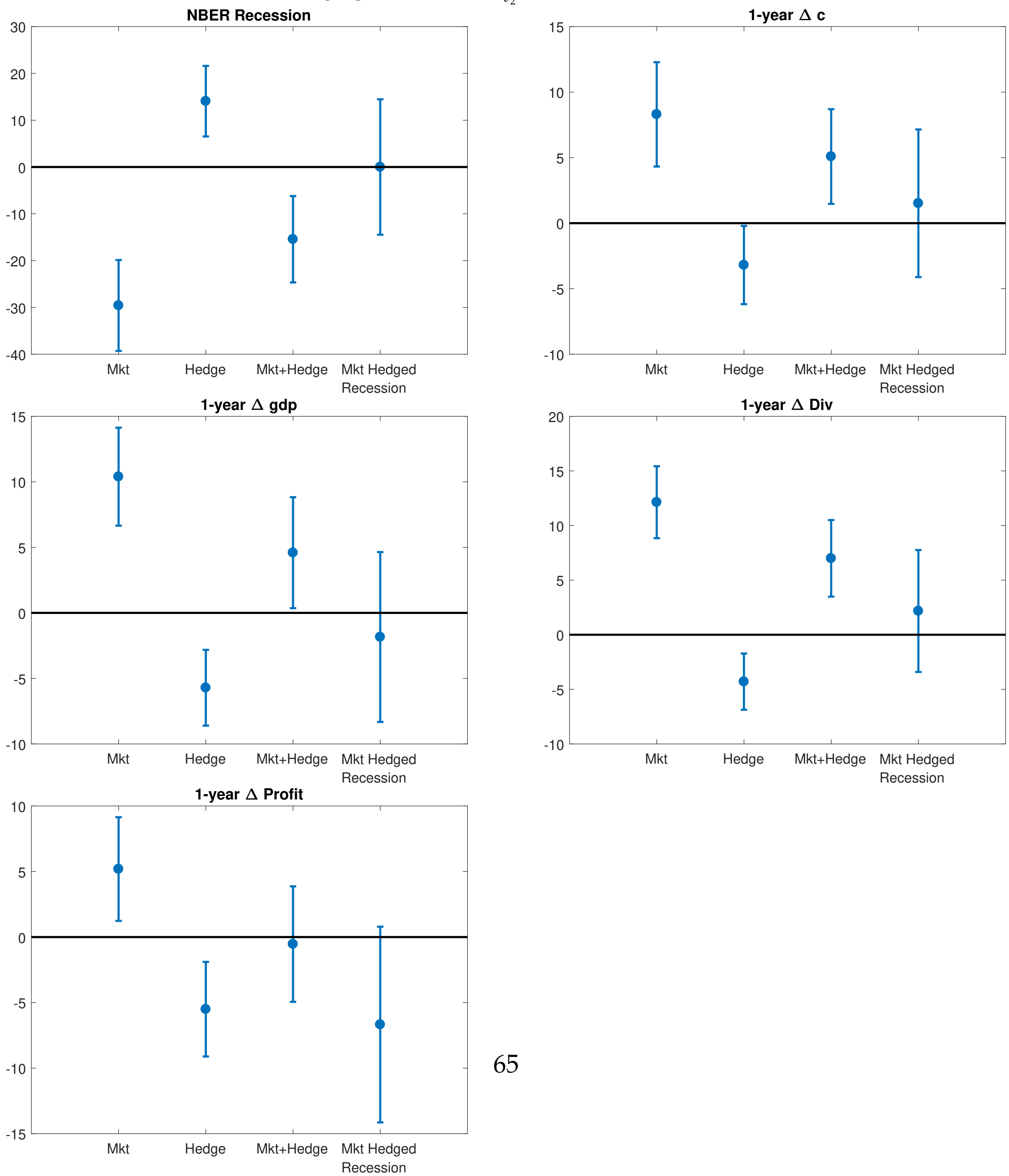


Figure A.3: Exposures of Macro Hedge Portfolio to Consumption-Based Factors: Controlling for Market Exposure in Pre-formation Beta Estimation.Here we control for the market portfolio when estimating pre-formation macro-factor betas. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. We plot exposures (and a 95% confidence interval) to several consumption factors for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$. See text for additional details. We plot exposure of our macro hedge to various business cycle and macroeconomic factors. The Consumption factors are Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017).

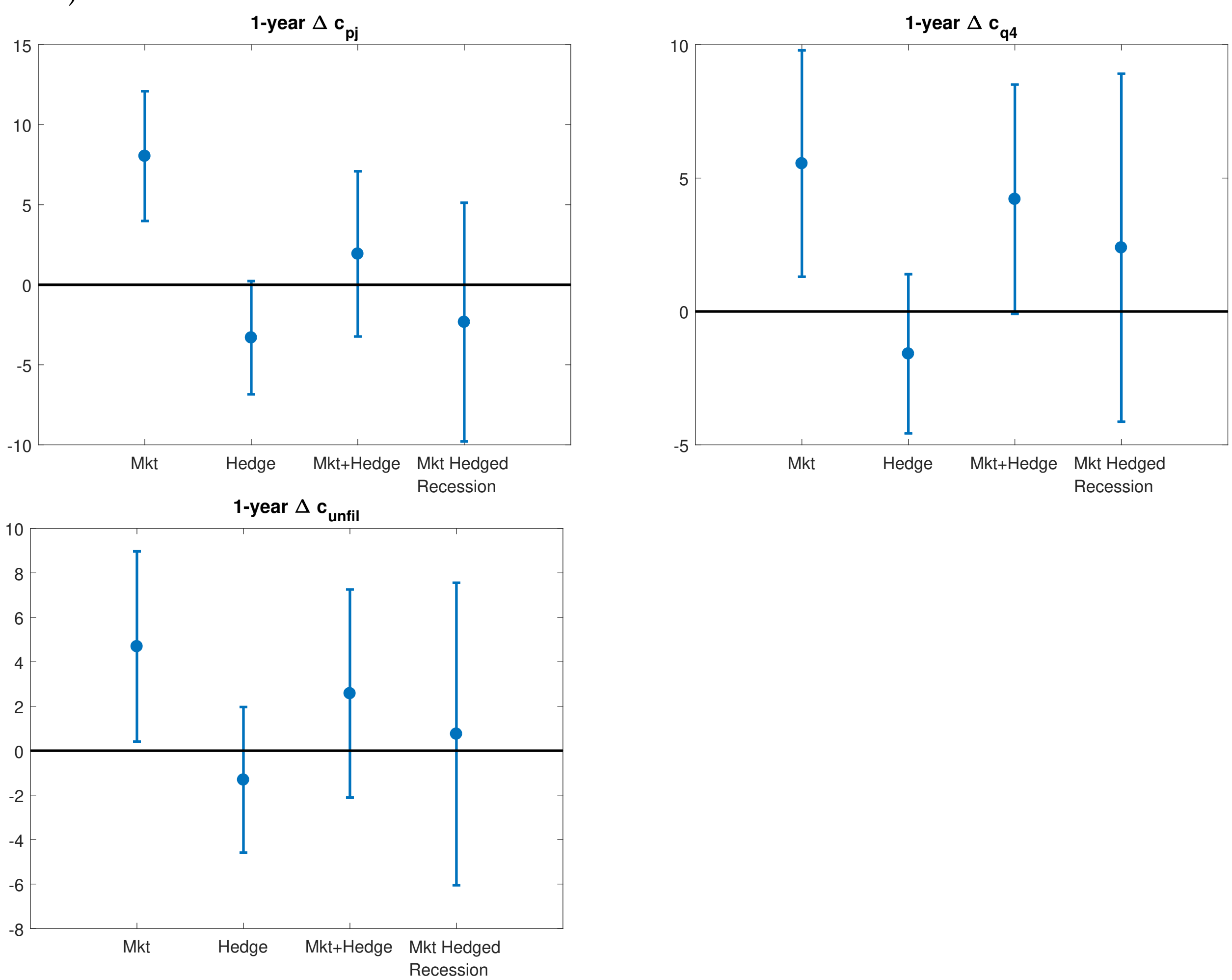


Figure A.4: Price of Risk Estimates of Leading Macro Factor Models: Controlling for Market Exposure in Pre-formation Beta Estimation. Here we control for the market portfolio when estimating pre-formation macro-factor betas. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. We plot prices of risk estimated from FF25 vs our ten macro hedge portfolios (formed by sorting on betas to our equal weight macro risk series, see text for details).We estimate this price of risk for Parker and Julliard (2005) (future consumption over three years, labeled "pj"), (Jagannathan and Wang, 2007) (fourth quarter to fourth quarter consumption, labeled "q4"), and (Kroencke, 2017) (unfiltered NIPA consumption, labeled "unfil"). Confidence bands are shown using Shanken standard errors.

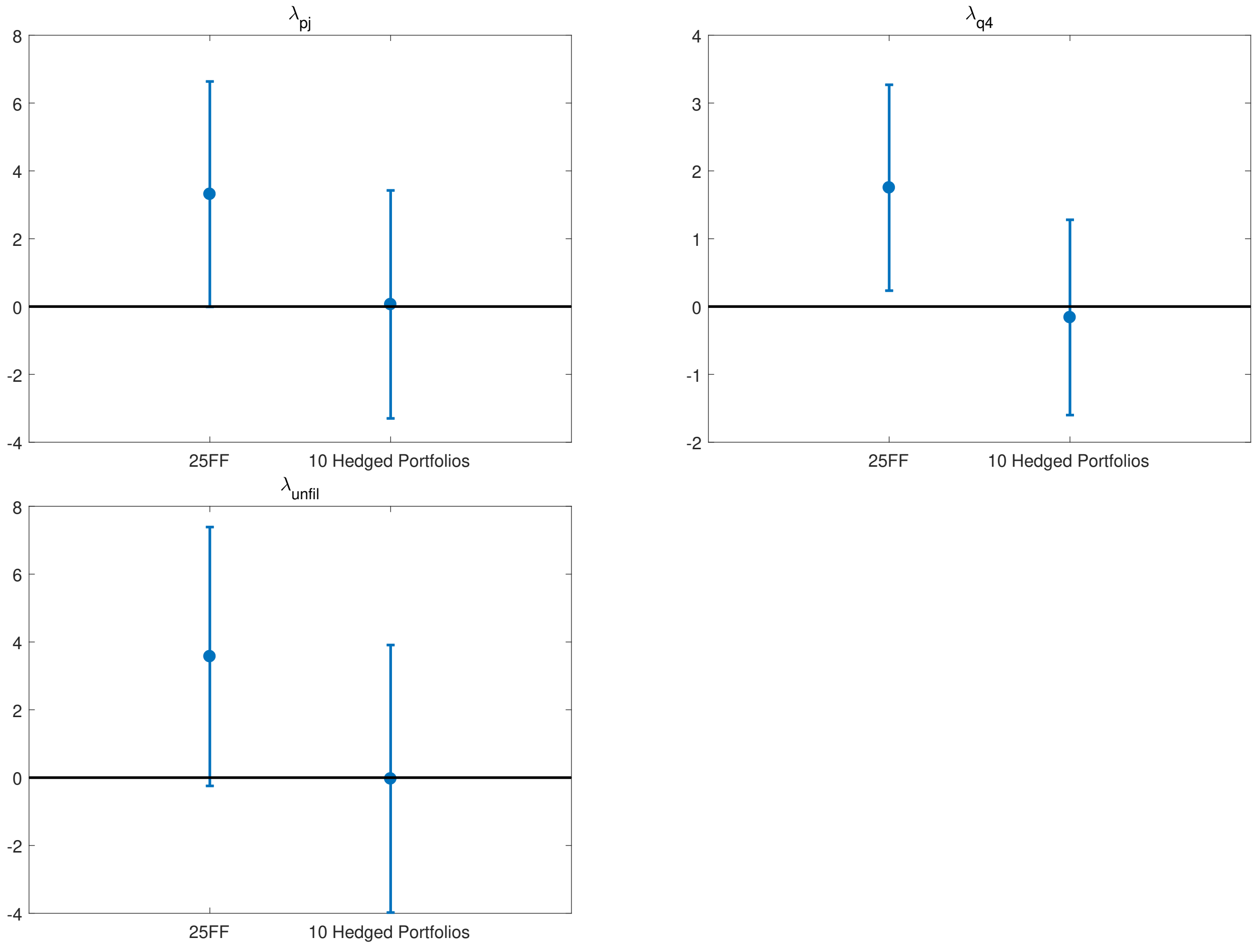


Figure A.5: Risk Premium of Macro Hedge Portfolios: Controlling for Market Exposure by Double Sorting. Here we control for the market portfolio when estimating pre-formation betas in order to hold fixed stocks exposure to the market portfolio. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. Then, we double sort stock based on both pre-formation betas and average across the market-beta quintiles. We plot the annualized average return and a 95% confidence interval for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure.

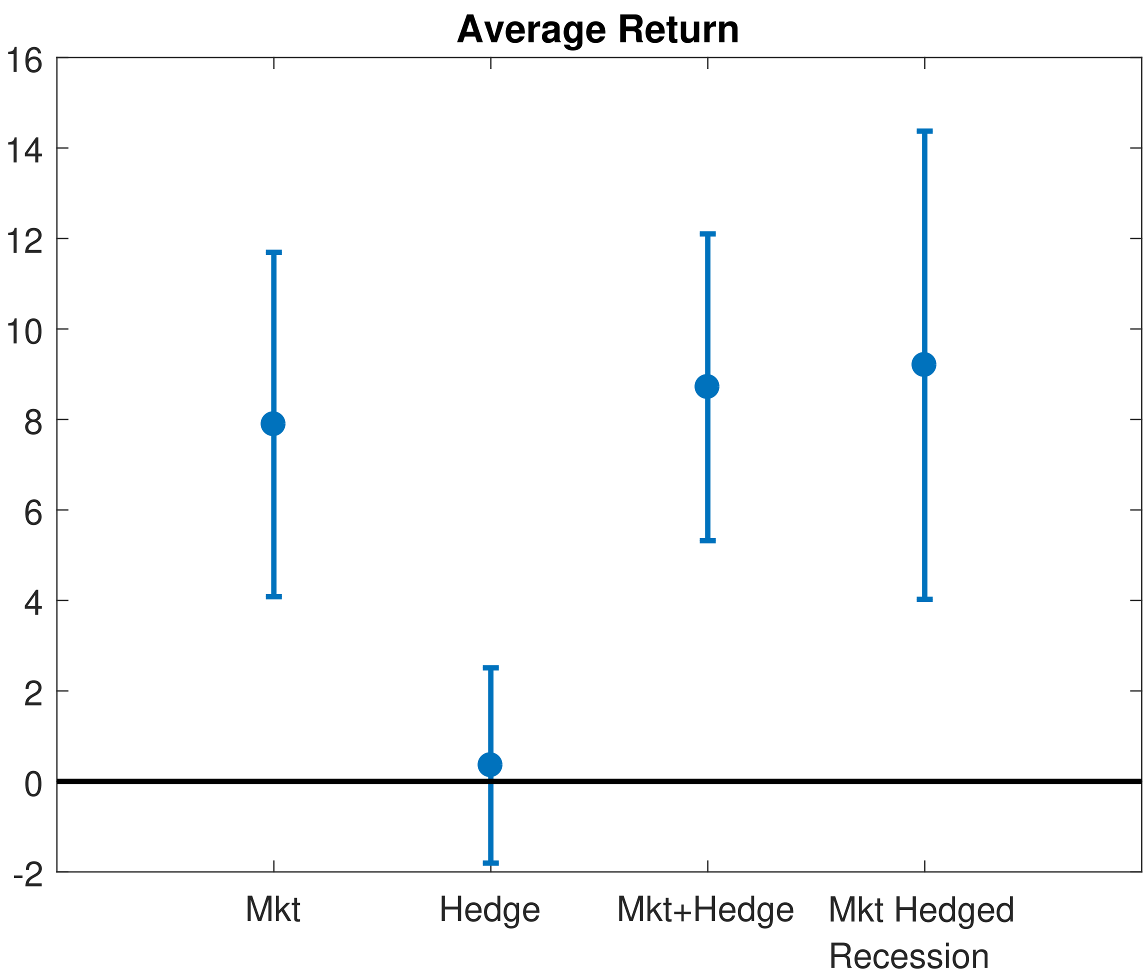


Figure A.6: Exposures of Macro Hedge Portfolio to Macro Variables: Controlling for Market Exposure by Double Sorting. Here we control for the market portfolio when estimating pre-formation betas in order to hold fixed stocks exposure to the market portfolio. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. Then, we double sort stock based on both pre-formation betas and average across the market-beta quintiles. We plot exposure of our macro hedge to various business cycle and macroeconomic factors. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$.

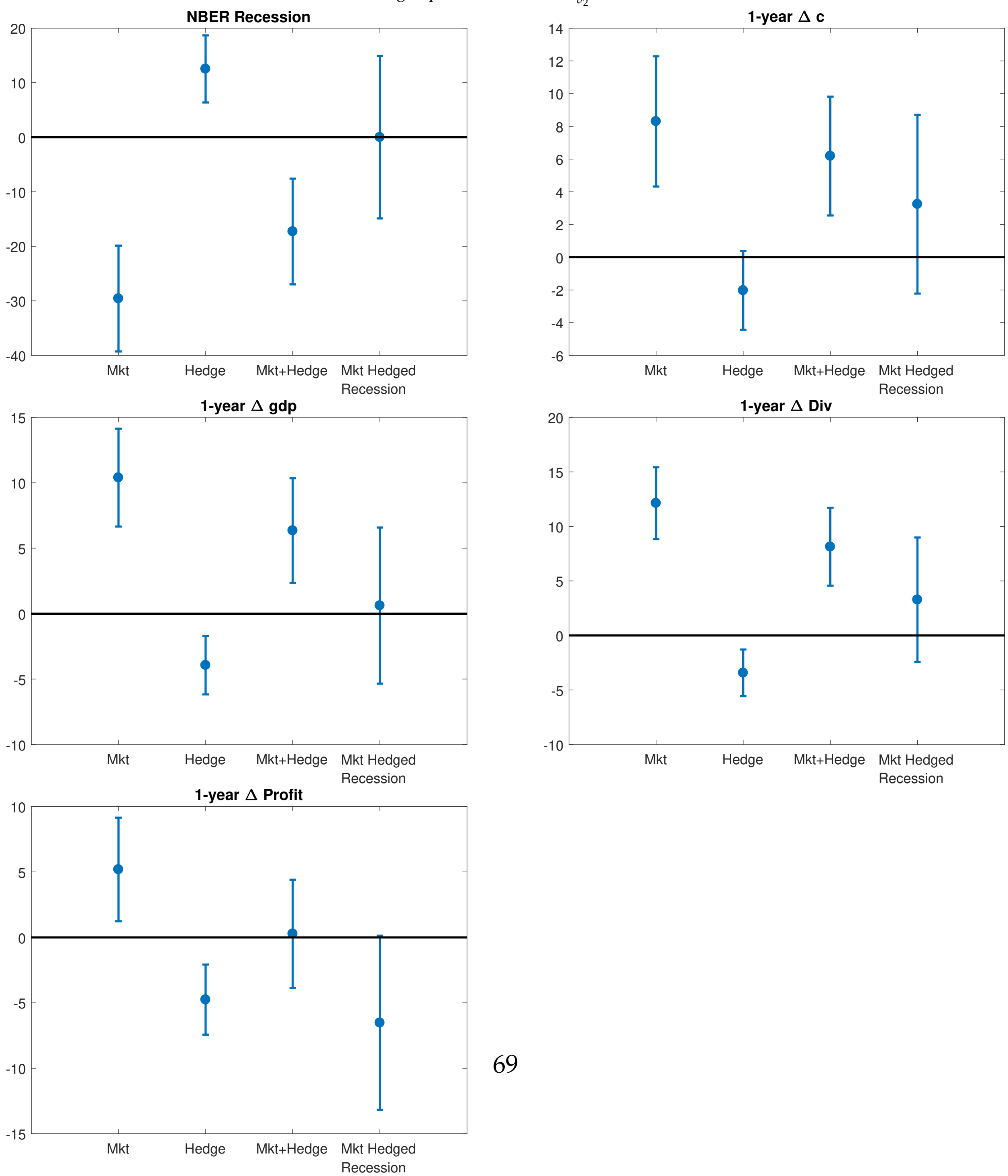


Figure A.7: Exposures of Macro Hedge Portfolio to Consumption-Based Factors: Controlling for Market Exposure by Double Sorting.. Here we control for the market portfolio when estimating pre-formation betas in order to hold fixed stocks exposure to the market portfolio. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. Then, we double sort stock based on both pre-formation betas and average across the market-beta quintiles. We plot exposure of our macro hedge to leading consumption factors. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$. See text for additional details. We control for the market portfolio when estimating pre-formation betas in order to hold fixed stocks exposure to the market portfolio. Then, we double sort stock based on both pre-formation betas and average across the market-beta quintiles. The consumption factor we report are Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017). Confidence bands are shown using Shanken standard errors.

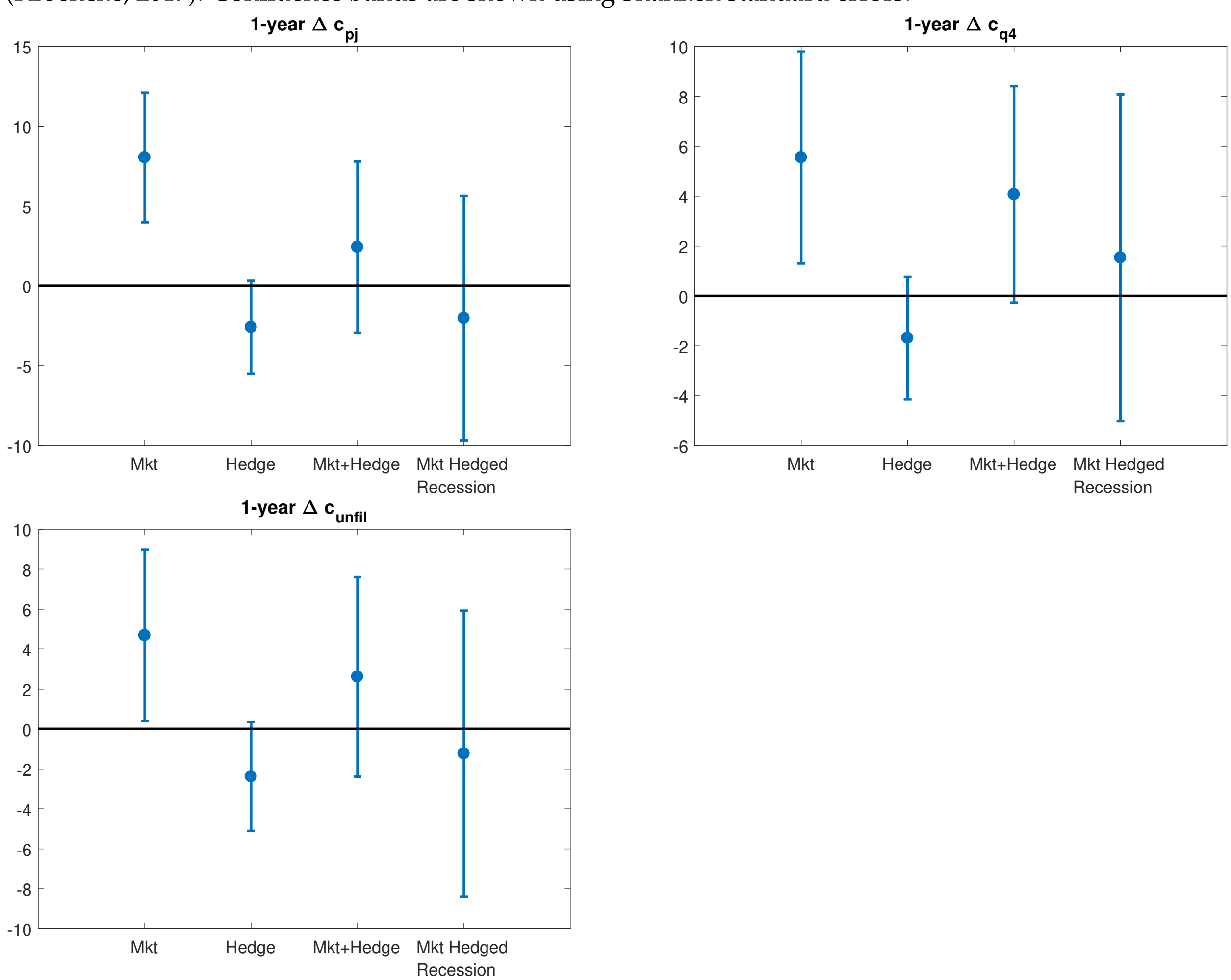


Figure A.8: Price of Risk Estimates of Leading Macro Factor Models: Controlling for Market Exposure by Double Sorting. Here we control for the market portfolio when estimating pre-formation betas in order to hold fixed stocks exposure to the market portfolio. Specifically we estimate rolling multi-variate regression with innovations in our macro-factor and the market return as a control. The rolling window is seven years. Then, we double sort stock based on both pre-formation betas and average across the market-beta quintiles. We plot prices of risk estimated from FF25 vs our ten macro hedge portfolios (formed by sorting on betas to our equal weight macro risk series, see text for details). We estimate this price of risk for Parker and Julliard (2005) (future consumption over three years, labeled "pj"), (Jagannathan and Wang, 2007) (fourth quarter to fourth quarter consumption, labeled "q4"), and (Kroencke, 2017) (unfiltered NIPA consumption, labeled "unfil"). Confidence bands are shown using Shanken standard errors.

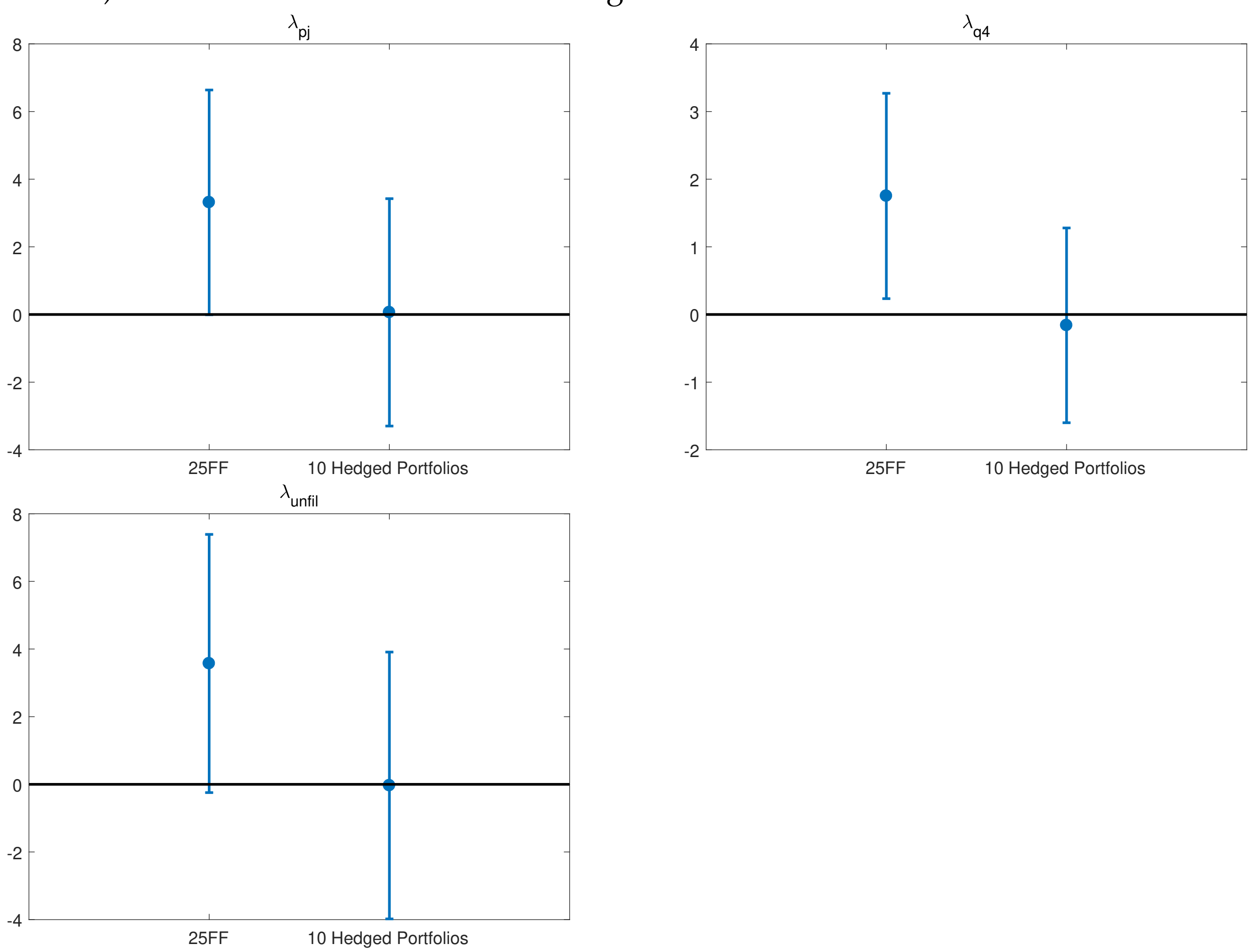


Figure A.9: Risk Premium of Macro Hedge Portfolios: Additional Hedging Portfolios. Here we construct macro-hedge portfolios based on the following additional factors:TED spread, Boats consumption, News implied volatility from (Manela and Moreira, 2017), and economic policy uncertainty from (Baker et al., 2016). We plot the annualized average return and a 95% confidence interval for the market portfolio and the macro hedge portfolios.

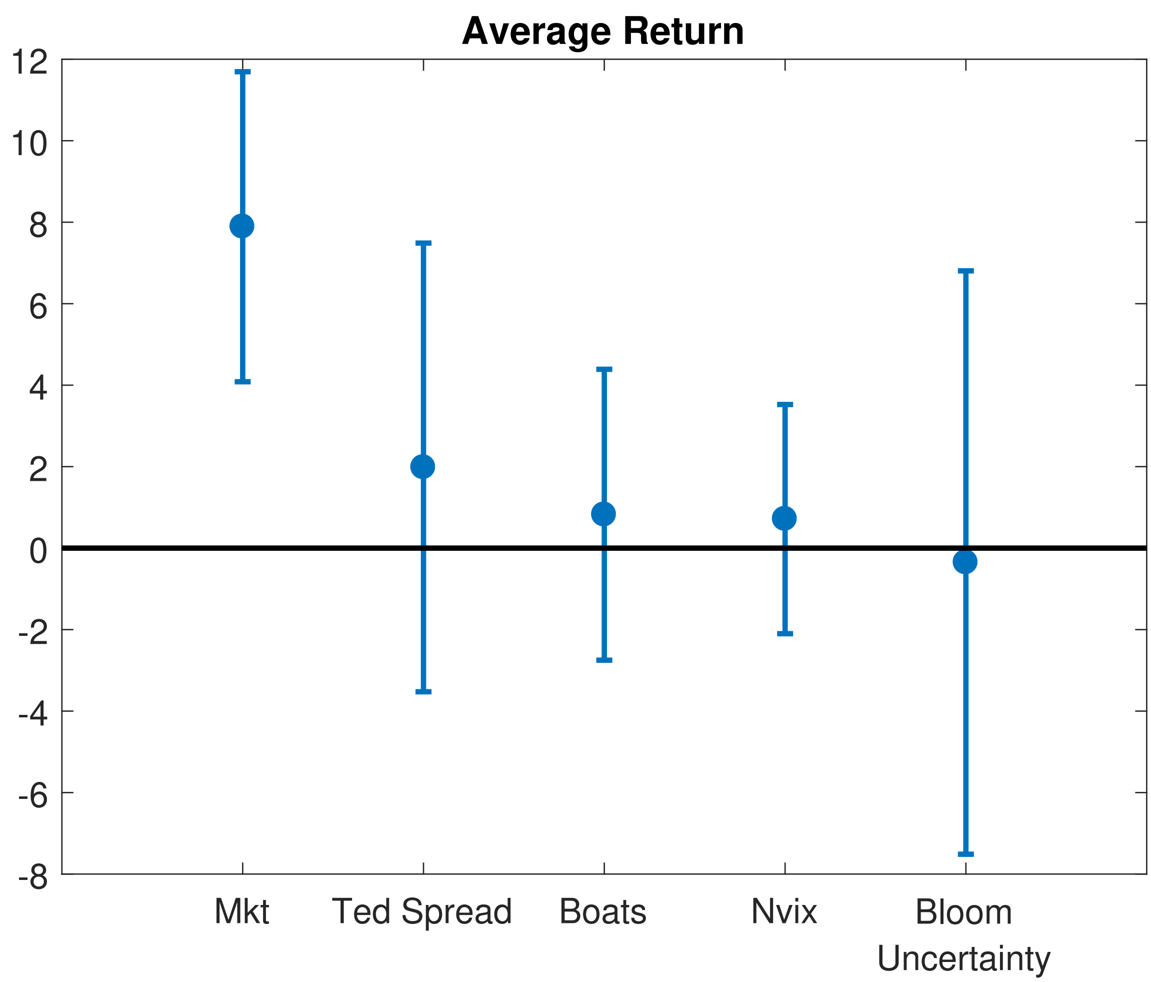


Figure A.10: Exposures of Macro Hedge Portfolio to Macro Variables: Additional Hedging Portfolios. Here we construct macro-hedge portfolios based on the following additional factors:TED spread, Boats consumption, News implied volatility from (Manela and Moreira, 2017), and economic policy uncertainty from (Baker et al., 2016). We plot exposure of our macro hedge to various business cycle and macroeconomic factors.

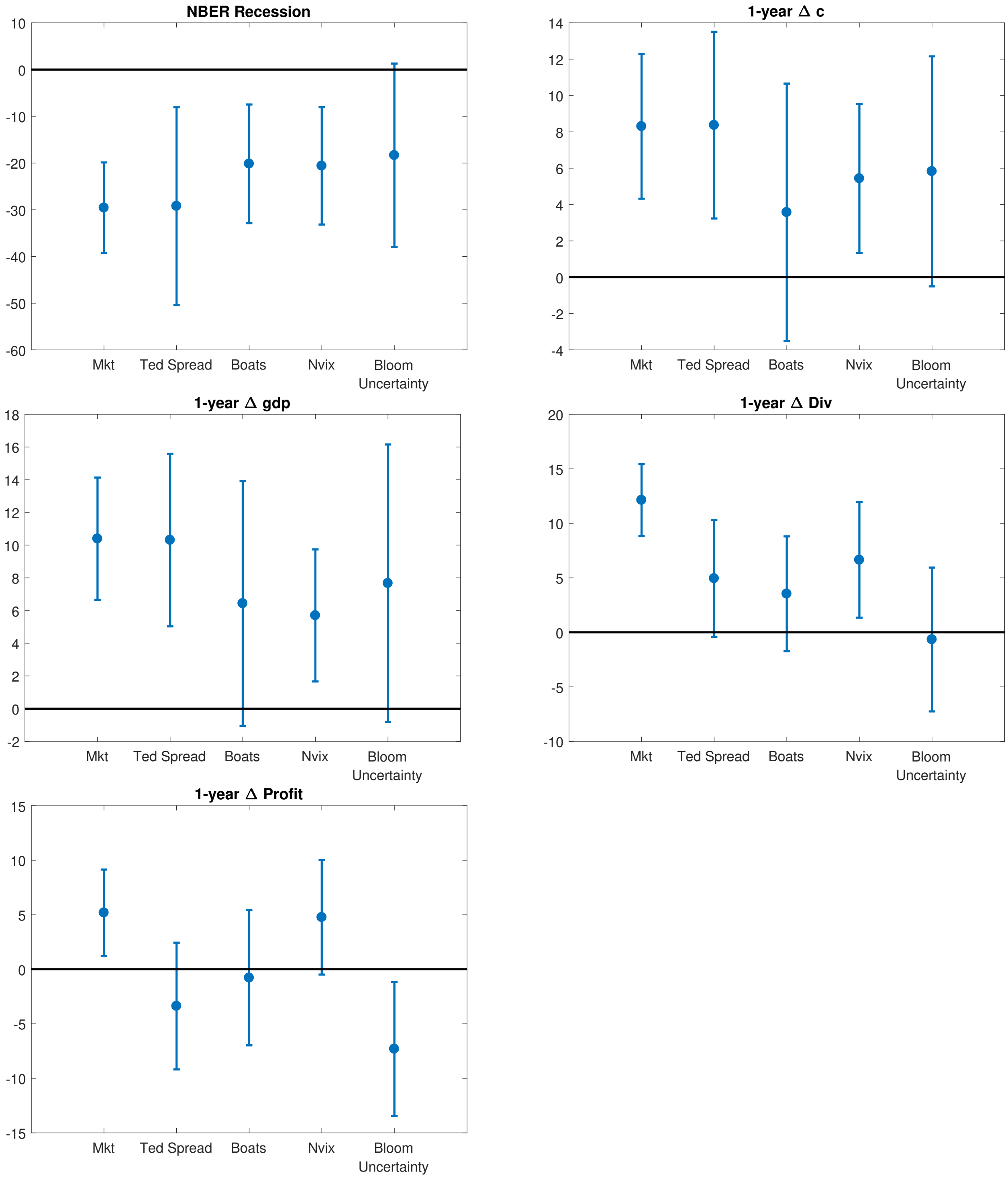


Figure A.11: Exposures of Macro Hedge Portfolio to Consumption-Based Factors: Additional Hedging Portfolios.. Here we construct macro-hedge portfolios based on the following additional factors:TED spread, Boats consumption, News implied volatility from (Manela and Moreira, 2017), and economic policy uncertainty from (Baker et al., 2016). We plot exposure to leading consumption factors. We report exposure to Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017).

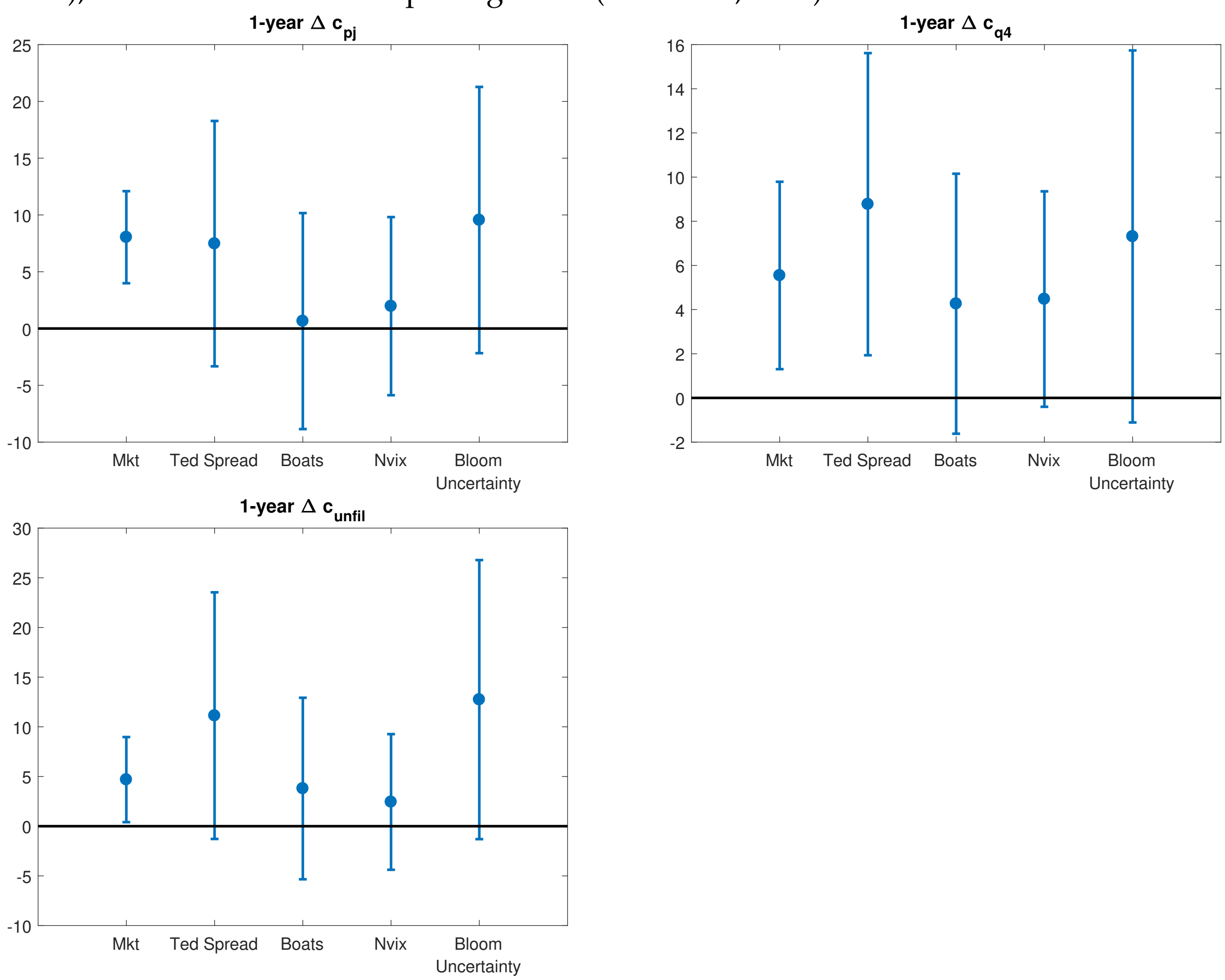


Figure A.12: Price of Risk Estimates of Leading Macro Factor Models: Additional Hedging Portfolios. Here we construct macro-hedge portfolios based on the following additional factors:TED spread, Boats consumption, News implied volatility from (Manela and Moreira, 2017), and economic policy uncertainty from (Baker et al., 2016). We plot prices of risk estimated from FF25 vs our ten macro hedge portfolios . We estimate this price of risk for Parker and Julliard (2005) (future consumption over three years, labeled "pj"), (Jagannathan and Wang, 2007) (fourth quarter to fourth quarter consumption, labeled "q4"), and (Kroencke, 2017) (unfiltered NIPA consumption, labeled "unfil"). Confidence bands are shown using Shanken standard errors.

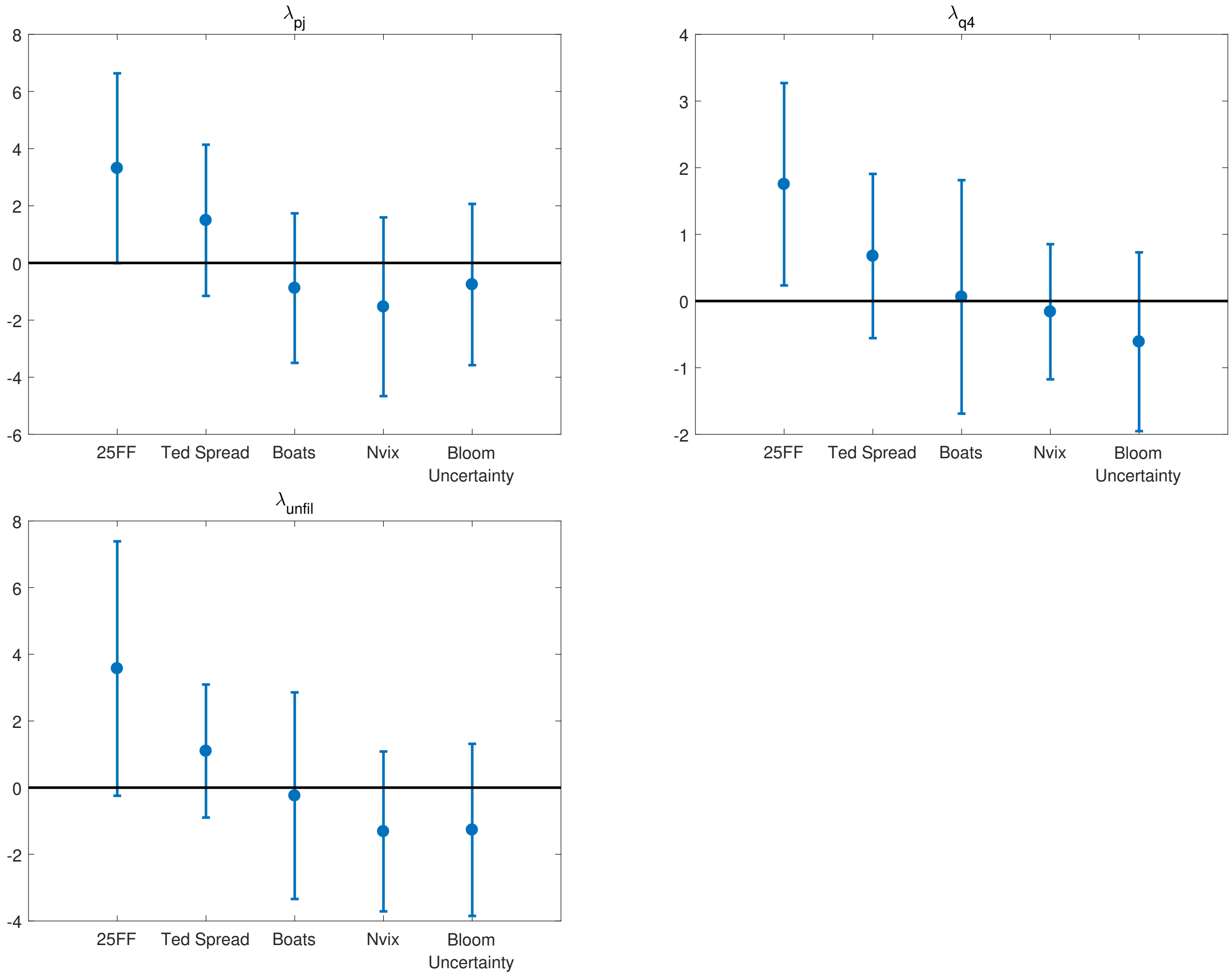


Figure A.13: Risk Premium of Macro Hedge Portfolios: Intermediary-Based Hedge Portfolios. Here we construct portfolios based on the intermediary-based factor of (He et al., 2017). We plot the annualized average return and a 95% confidence interval for the market portfolio, and the macro hedge portfolios with respect to the intermediary-based factors of (He et al., 2017). We label HKM1 their non-trade factor and HKM2 the traded version. We focus on (He et al., 2017) instead of (Adrian et al., 2014) to construct our hedge portfolio because (Adrian et al., 2014) factor is available only at the quarterly frequency. Our macro hedge is a low minus high portfolio based on past exposure to HKM1 and HKM2.

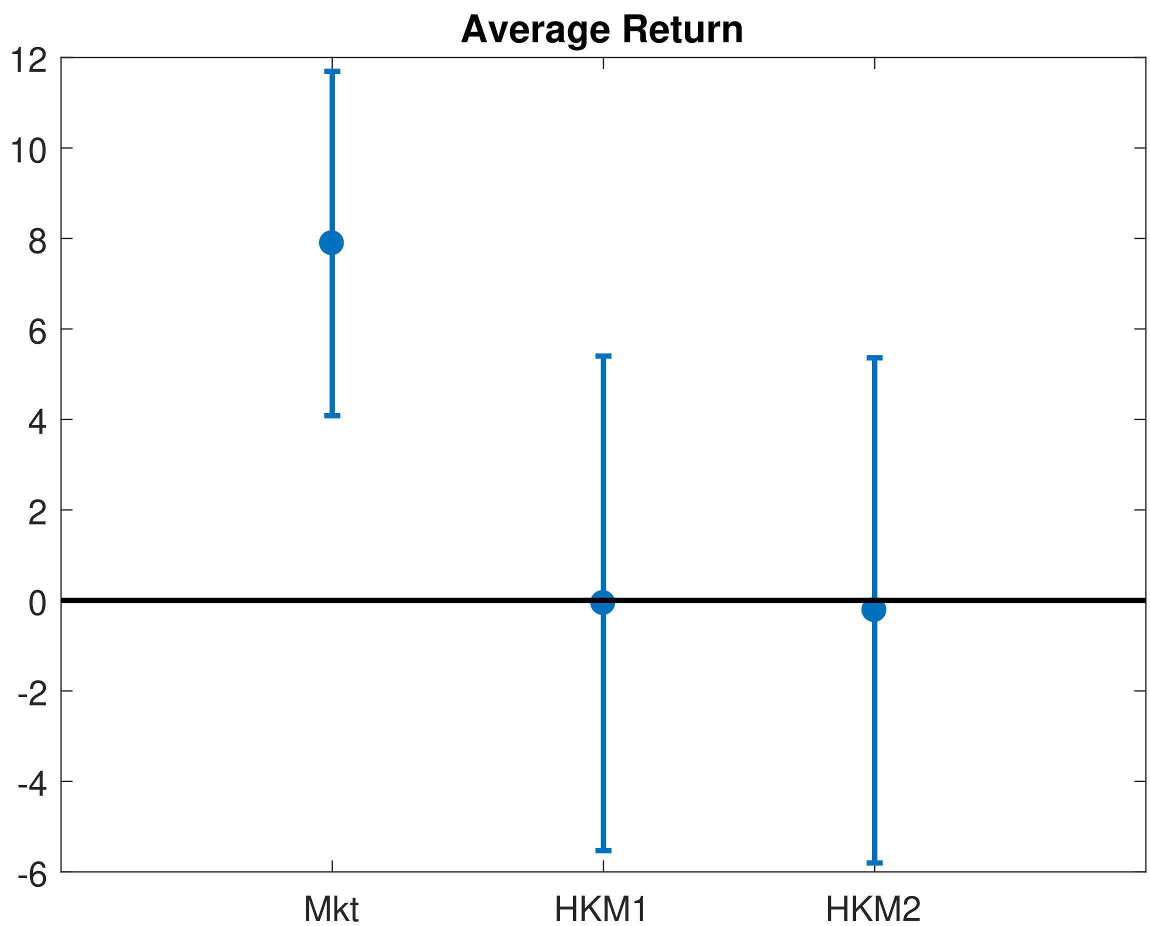


Figure A.14: Exposures of Macro Hedge Portfolio to Macro Variables: Intermediary-Based Hedge Portfolios.. Here we construct portfolios based on the intermediary-based factor of (He et al., 2017). We plot exposure of our macro hedge to various business cycle and macroeconomic factors. Our macro hedge is a low minus high portfolio based on past exposure to the intermediary-based factors of (He et al., 2017). We label HKM1 their non-trade factor and HKM2 the traded version. We focus on (He et al., 2017) instead of (Adrian et al., 2014) to construct our hedge portfolio because (Adrian et al., 2014) factor is available only at the quarterly frequency.

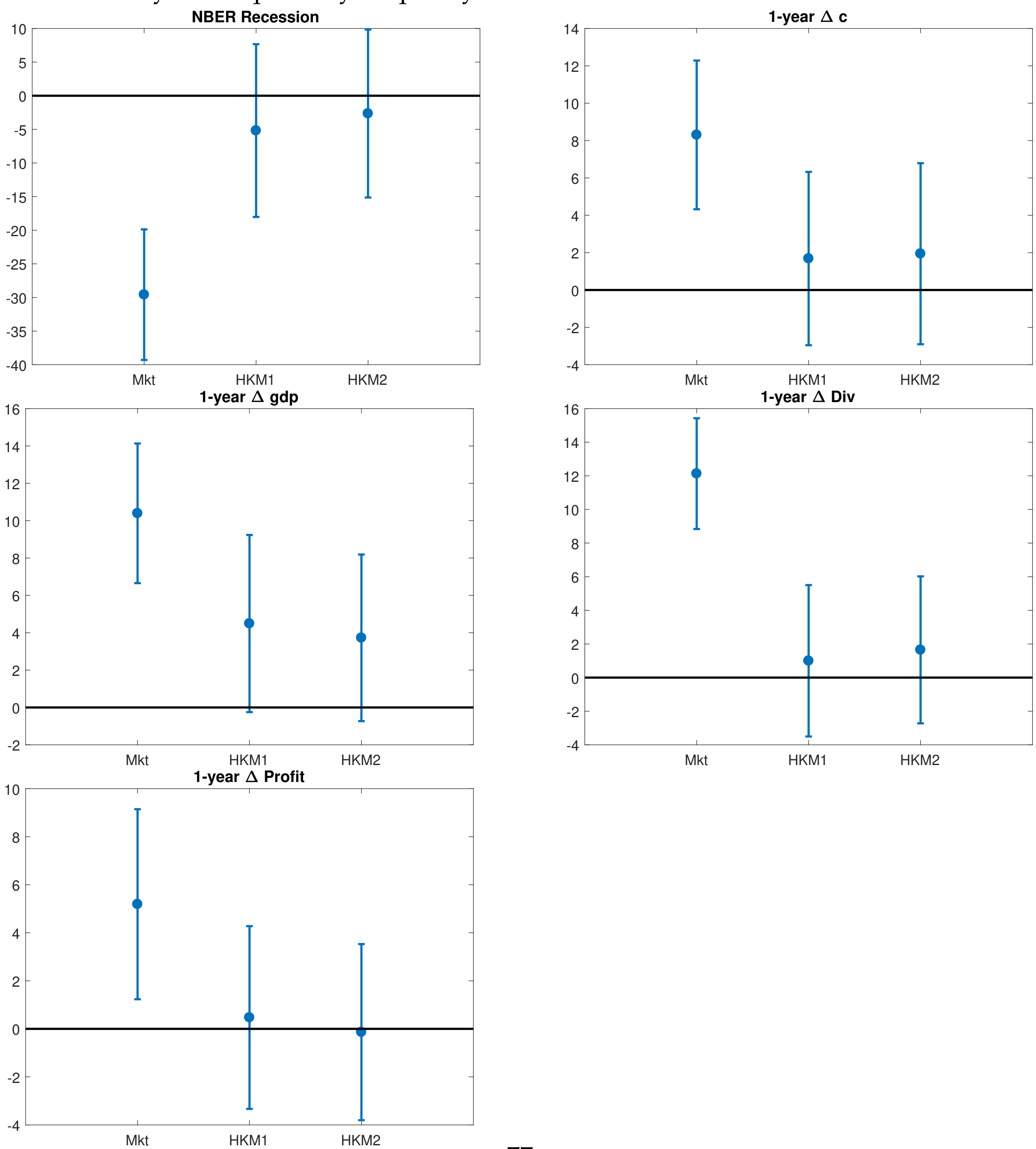


Figure A.15: Exposures to Consumption-Based Factors: Intermediary-Based Hedge Portfolios. Here we construct portfolios based on the intermediary-based factor of (He et al., 2017). We plot exposure of our macro hedge to various business cycle and macroeconomic factors. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. We control for the market portfolio when estimating pre-formation betas in order to hold fixed stocks exposure to the market portfolio. Then, we double sort stock based on both pre-formation betas and average across the market-beta quintiles. We report exposure to Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017).

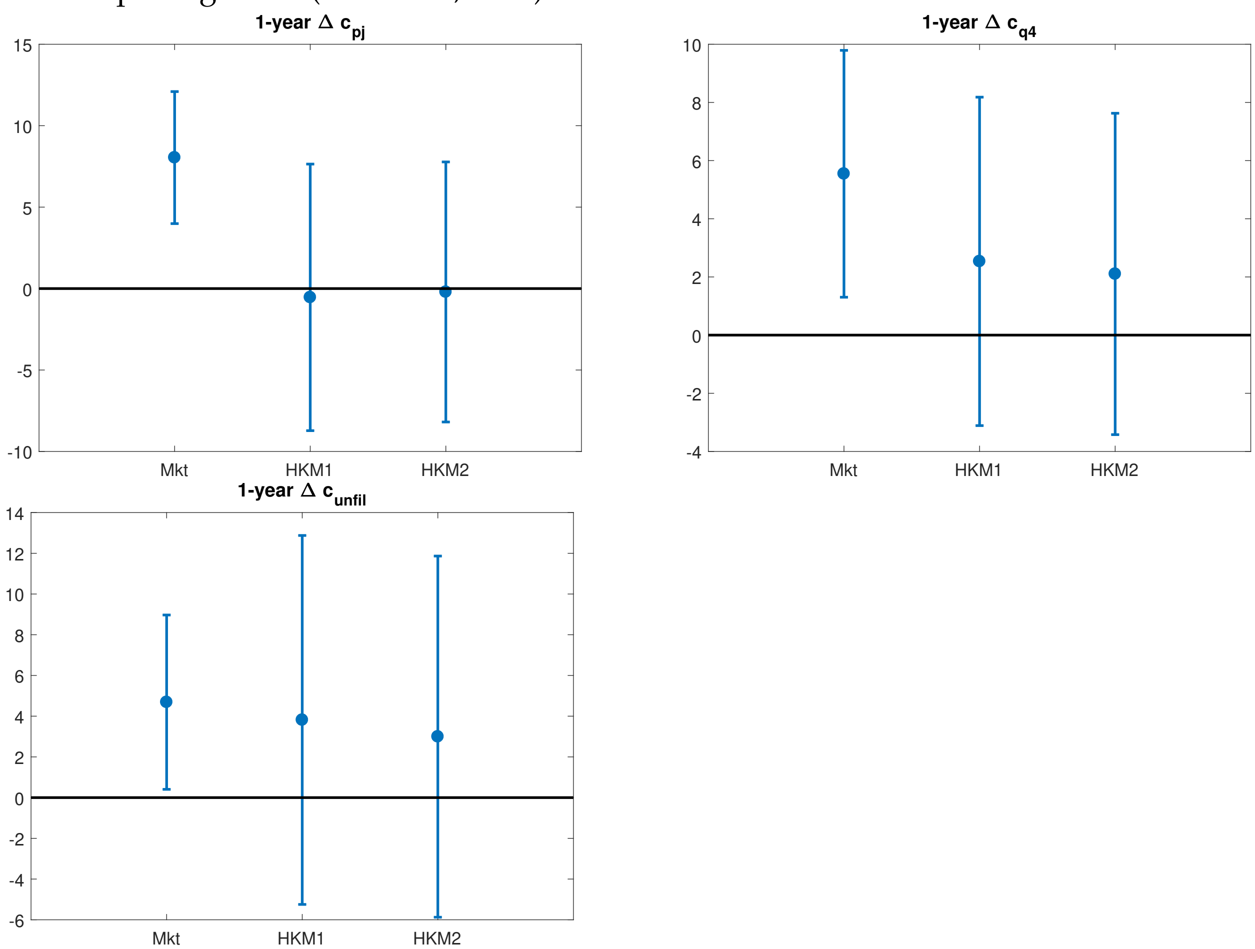


Figure A.16: Price of Risk Estimates of Leading Macro Factor Models: Intermediary-Based Hedge Portfolios. Here we construct portfolios based on the intermediary-based factor of (He et al., 2017). We plot prices of risk estimated from FF25 vs our ten macro hedge portfolios (formed by sorting on betas to our equal weight macro risk series, see text for details). Our macro hedge is a low minus high portfolio based on past exposure to the intermediary-based factors of (He et al., 2017). We label HKM1 their non-trade factor and HKM2 the traded version. We focus on (He et al., 2017) instead of (Adrian et al., 2014) to construct our hedge portfolio because (Adrian et al., 2014) factor is available only at the quarterly frequency. We estimate this price of risk for Parker and Julliard (2005) (future consumption over three years, labeled "pj"), (Jagannathan and Wang, 2007) (fourth quarter to fourth quarter consumption, labeled "q4"), (Kroencke, 2017) (unfiltered NIPA consumption, labeled "unfil"), , and the intermediary-based factor models from (Adrian et al., 2014) and (He et al., 2017) . Confidence bands are shown using Shanken standard errors.

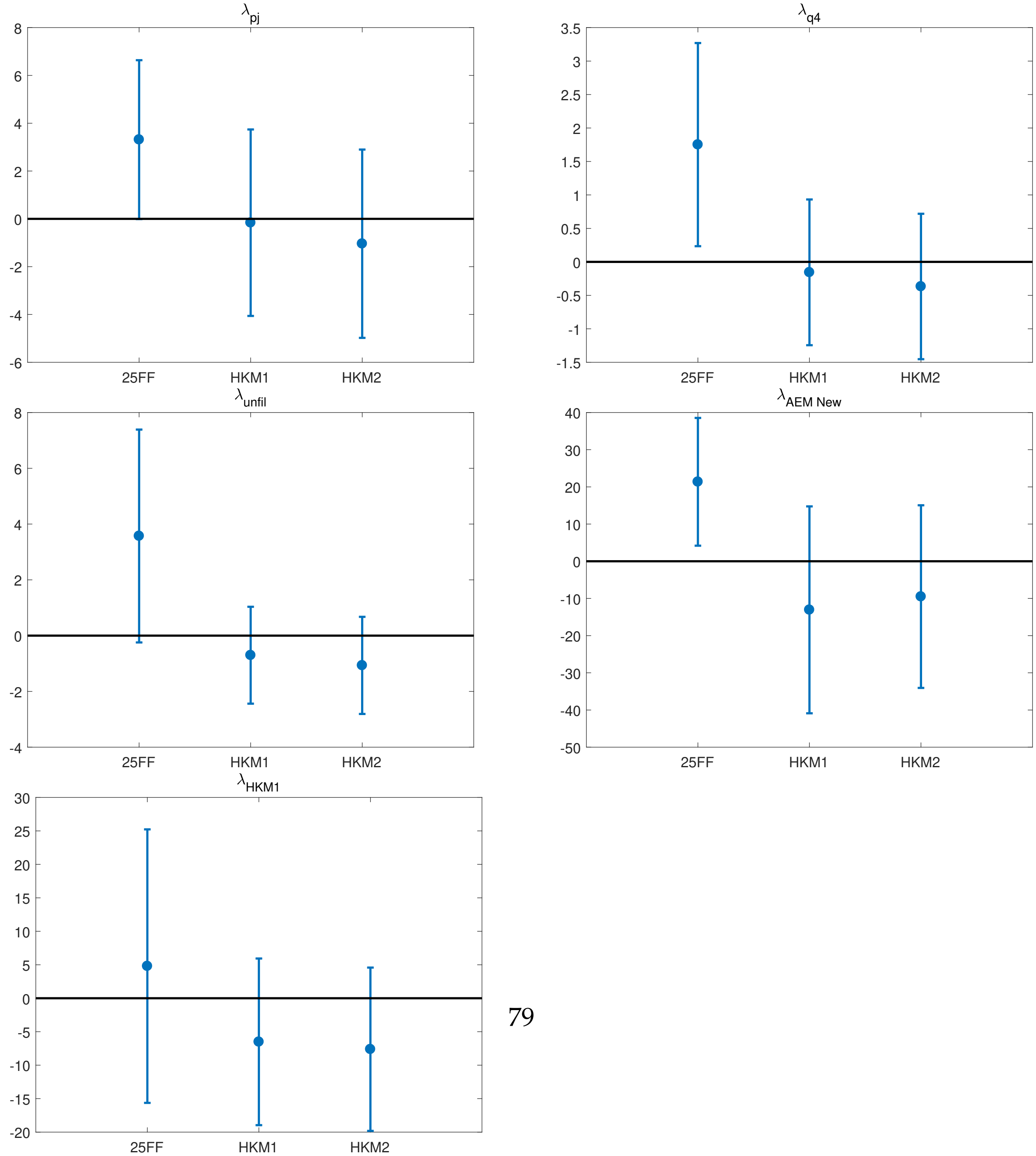


Figure A.17: Risk Premium of Macro Hedge Portfolios: Alternative Beta Estimation. Here we estimate betas using a rolling window of seven years using only monthly data. We plot the annualized average return and a 95% confidence interval for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$.

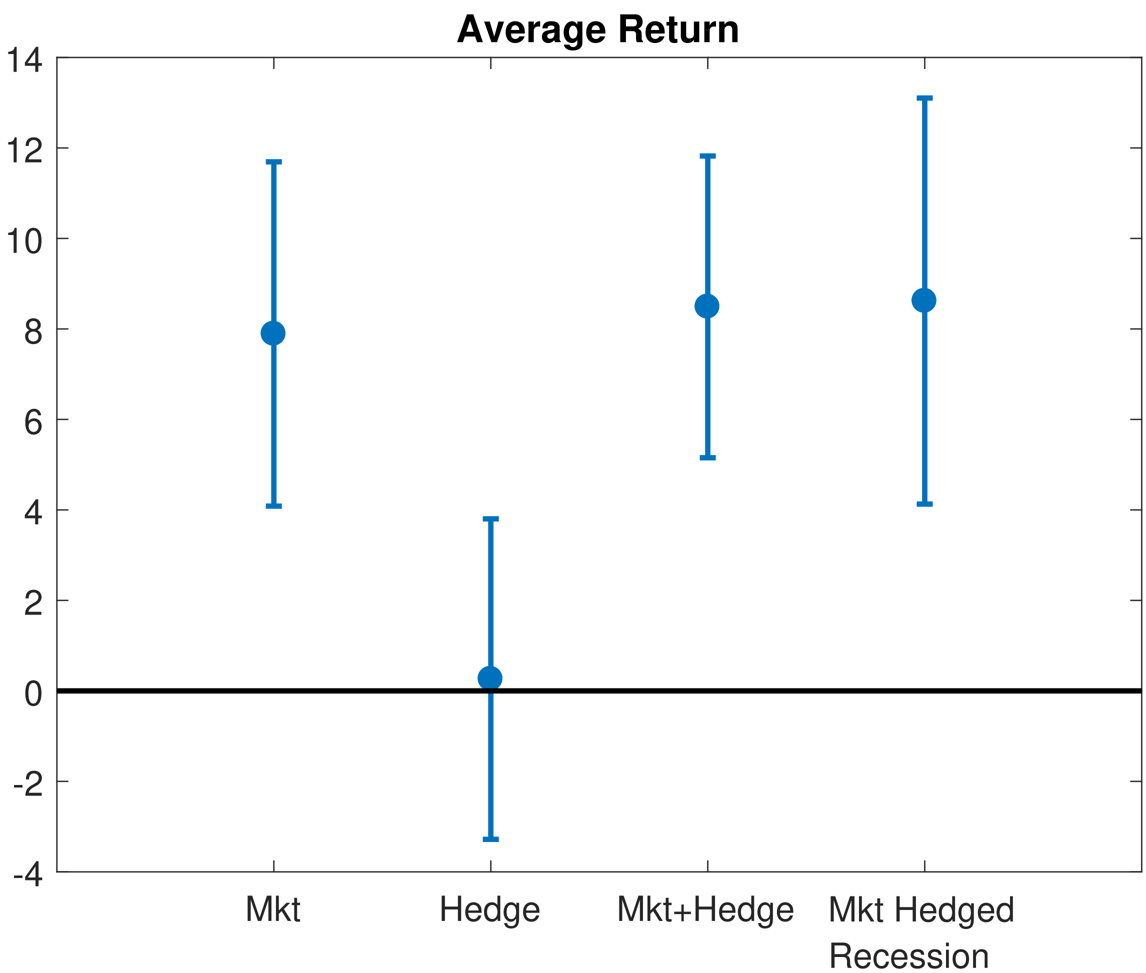


Figure A.18: Exposures of Macro Hedge Portfolio to Macro Variables: Alternative Beta Estimation.. Here we estimate betas using a rolling window of seven years using only monthly data. We plot exposures to various macroeconomic factors (and a 95% confidence interval) for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$.

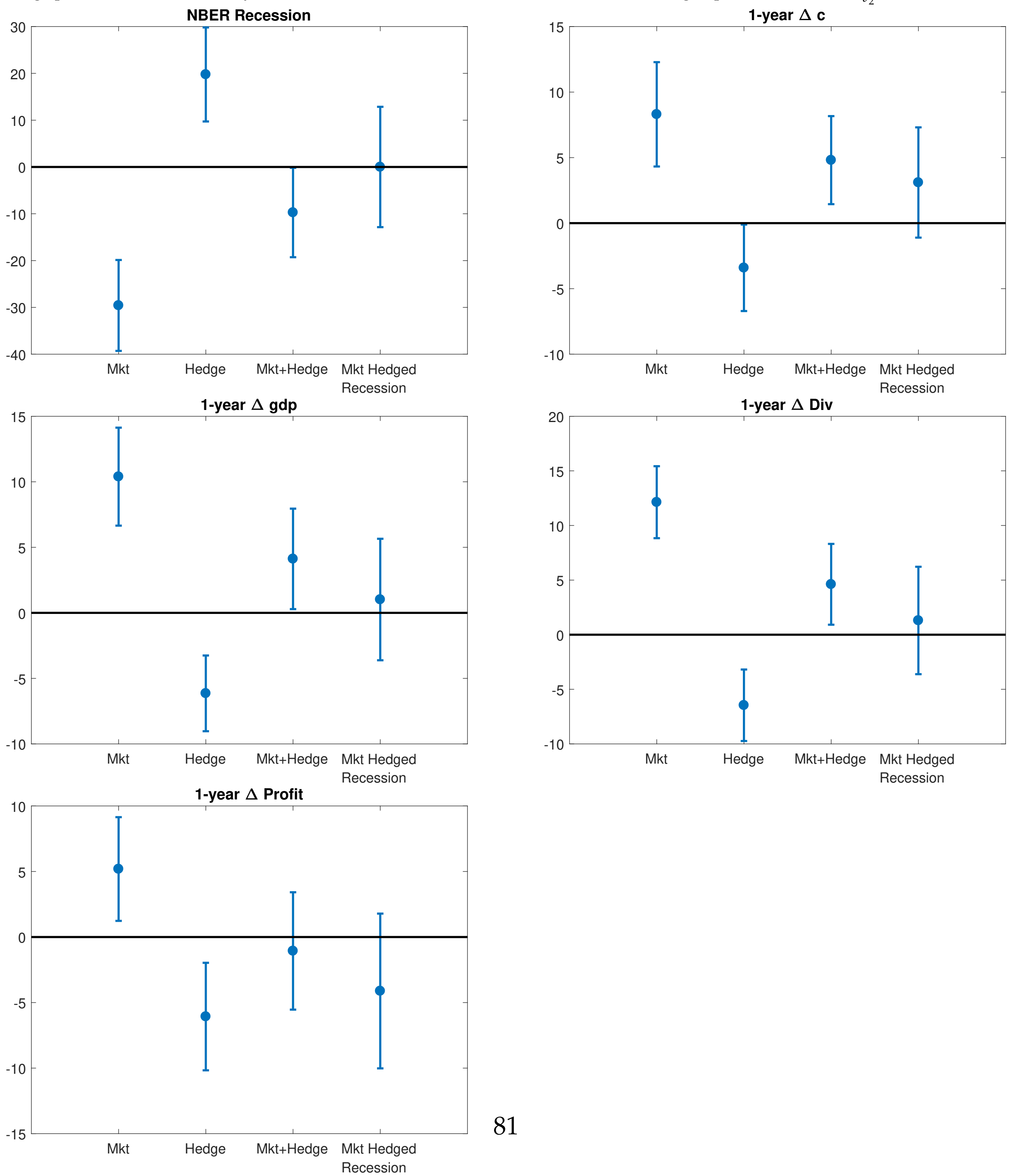


Figure A.19: Exposures of Macro Hedge Portfolio to Consumption-Based Factors: Alternative Beta Estimation. Here we estimate betas using a rolling window of seven years using only monthly data. We plot exposures (and a 95% confidence interval) to several consumption factors for the market portfolio, the macro hedge portfolio, the market portfolio plus the macro hedge and the recession hedged portfolio. Our macro hedge is a low minus high portfolio based on past exposure to macroeconomic conditions that combine industrial production, initial claims, credit spreads, and the slope of the term structure. The recession hedged portfolio uses the in sample recession exposure of the hedge portfolio and market portfolios to construct a recession hedged version of the market portfolio. Specifically, if the market has sensitivity δ_1 to a recession event, and the hedge portfolio has δ_2 sensitivity to a recession event, than we construct the recession hedged portfolio as $R^{mkt} - \frac{\delta_1}{\delta_2} R^{Hedge}$. See text for additional details. We plot exposure of our macro hedge to various business cycle and macroeconomic factors. The Consumption factors are Parker and Julliard (2005) consumption factor , Q4 to Q4 consumption growth (Jagannathan and Wang, 2007), and unfiltered consumption growth (Kroencke, 2017).