Risk-Return Expectations of Financial Intermediaries

This version: August 22, 2023

Abstract

I study differences in risk and return expectations of financial intermediaries and non-intermediaries. I find that return expectations reported in surveys do not exhibit significant differences. Risk expectations are substantially lower than the realized risk in the stock market for both, but the underestimation is less pronounced for intermediaries. Intermediaries constantly have higher risk expectations than non-intermediaries, primarily driven by higher perceived downside risk. To test the survey evidence in the cross-section of asset returns, I present an asset pricing model with an intermediary sector and biased risk beliefs. I derive a testable prediction when intermediaries have higher risk expectations than households. In line with this prediction, I find a return premium for stocks with high institutional ownership when the wedge in risk expectations widens.

JEL classification: G12, G20, G40

1. Introduction

Subjective return and risk expectations reported in surveys do not align well with rational expectations commonly assumed in standard asset pricing models. For instance, the average survey participant has return expectations with too low volatility (De La O and Myers, 2021; Nagel and Xu, Forthcoming) and sticky risk expectations (Lochstoer and Muir, 2022). This survey evidence only challenges rational expectation models if the biased expectations of the average survey participant impact those of the marginal representative investor. Financial intermediaries (FIs) are the natural candidates as marginal investors, as financial frictions in the economy impede the average household from investing in certain asset markets.[1] If this is the case, the question arises whether subjective expectations of FIs differ from the average non-intermediary (non-FI), as only the former is crucial in determining asset prices. Therefore, this paper studies the properties of FI expectations, analyzes how they differ from the average non-FI, and tests the implications for the cross-section of stock returns.

This paper presents three novel facts about the differences in expectations of FIs and non-FIs. First, nominal return expectations of FIs and non-FIs are similar and procyclical. Second, FIs constantly have higher risk expectations than non-FIs. This wedge is especially pronounced in good times, while the expectations align well in bad times. The higher risk expectations are primarily due to elevated perceived downside risks of financial intermediaries. Third, FIs and non-FIs both severely underestimate the true risk in the stock market, confirming previous evidence for the average survey participant (Ben-David, Graham, and Harvey, 2013). To test the survey evidence in the cross-section of asset returns, I present an asset pricing model with an intermediary sector and biased risk beliefs, where the household faces costs when holding risky assets directly. If intermediaries have higher risk expectations than households, the model predicts that asset returns increase in the intermediation costs when the wedge in risk expectations widens. This result follows from the relatively low demand of intermediaries in this

[1] He and Krishnamurthy (2018) provide a review of the intermediary asset pricing literature.

case, so costly assets have higher returns to incentivize intermediaries to hold a larger share. In contrast, if intermediaries' risk expectations are lower, the intermediary demand relatively rises when the wedge in risk expectations increases, and costly assets have lower returns to force households to take a higher share. I provide empirical evidence supporting the prediction of higher intermediary risk expectations in the cross-section of stock returns with 498,045 stock-month observations. Overall, this paper shows that return expectations of FIs and non-FIs are similar, while risk expectations differ, and that this difference significantly affects the cross-section of stock returns.

I study differences in expectations using the CFO Graham-Harvey survey from 2001 to 2018 (see, e.g., Ben-David et al., 2013). This quarterly survey asks CFOs and financial executives of US firms about their expectations for the economy. The survey offers two advantages for analyzing expectations: first, it reports expectations about first- and second-order moments of the S&P 500 over one year. Therefore, it allows for studying return and risk expectations, which are highly relevant for asset prices. Second, survey participants self-report the industry of their company. This allows me to distinguish between FIs and non-FIs. This exercise is subject to some identifying assumptions. First, CFOs report real expectations about the stock market and do not misreport because of exogenous reasons. I provide evidence that there is no CFO-specific misreporting, as I successfully replicate recent findings in the literature that uses other survey data. Second, CFOs of firms in the financial industry are better proxies for the expectations of FIs than CFOs from other industries like manufacturing or technology. I argue that CFOs from the financial industry acquire information within their firm, which includes trading desks and research departments. Thus, they should be at least *better* proxies for intermediary expectations than CFOs from other industries.

Nominal return expectations of FIs and non-FIs do not differ in their level or time-series variation. Both nominal return expectations are pro-cyclical, as they are significantly correlated with various business cycle indicators. To account for the fact of time-varying interest rates, I also test the cyclicality of excess return expectations under the assumption that the risk-free rate is known to the survey participants (Dahlquist and Ibert, 2023).

Excess return expectations do not exhibit any cyclicality and are, therefore, constant over time. In intermediary asset pricing models (He and Krishnamurthy, 2019), (excess) return expectations of FIs should be counter-cyclical so that expected returns increase in crisis times. Thus, the survey evidence does not align well with rational expectations in equilibrium intermediary asset pricing models.

Second, I study the wedge in risk expectations of FIs and non-FIs. Besides their average expectation, survey participants also report their expectations about the first and ninth deciles of the return distribution. The difference between the two should be correlated with expected volatility, while the first (ninth) decile is a direct measure of downside (upside) risk (potential). Risk expectations of FIs are consistently higher than those of non-FIs. On average, the inter-decile range from the ninth to the first decile return is 13% higher for FIs than non-FIs. The variation in risk expectations and the difference in risk levels primarily stems from the first decile of the return. Thus, FIs constantly perceive a higher downside risk in the economy, leading to an overall higher risk assessment compared to non-FIs. In the time series, regressions of risk expectations on various business cycle indicators suggest a counter-cyclical behavior as suggested by standard models. However, the wedge between FIs and non-FIs is pro-cyclical, as the overall difference in risk expectations reduces in bad times.

Third, I compare the risk expectations of FIs and non-FIs to the historical realized distribution of one-year S&P 500 returns. FIs and non-FIs severely underestimate the realized risk in the stock market. The expected first decile return is 11.8 pp (12.9 pp) too optimistic for FIs (non-FIs), while the upper expected decile return is 17.6 pp (18.1 pp) too pessimistic. Under the assumption of normally distributed yearly returns, this corresponds to an underestimation of actual volatility by more than 11.4 pp (12 pp). Thus, the volatility expectations of FIs (non-FIs) are 67% (70%) lower compared to the realized historical average.

The survey evidence suggests that FIs have higher risk expectations than non-FIs. To test this finding in the cross-section of asset returns, I present an asset pricing model with an intermediary sector and biased risk beliefs. This modeling choice nests the model of Haddad and Muir (2021) as a special case with rational expectations. The intermediary and the household optimize their demand based on mean-variance preferences, where the intermediary passes through its payoffs. However, the household does not control the investment decisions of the intermediary, as the intermediary faces constraints that affect his investment decisions independently, e.g., equity or debt constraints (He and Krishnamurthy, 2013; Adrian and Shin, 2014; Brunnermeier and Sannikov, 2014). The household can either trade through the intermediary costlessly or directly in the assets with costs. The household appreciates when the intermediary holds more costly assets due to lower costs through direct holdings. The intermediary and household may disagree about the risk of the assets, even though both observe the same signal.

The model makes opposing predictions for the cross-section of asset returns, depending on whether the intermediary has higher or lower risk expectations than the household. If the intermediary has higher (lower) risk expectations than the household, the returns of assets with high intermediation costs are higher (lower) when the wedge in risk expectations widens. The intermediary demand is relatively low for higher intermediary risk beliefs, and the household must hold a high share in costly assets. When a signal enters the market that widens the wedge in risk expectations of the intermediary and the household, the returns of costly assets are higher to increase the share of the intermediary. In contrast, if the intermediary has lower risk expectations than the household, the intermediary demand is relatively high, and the household must substitute his demand. However, the household's willingness to substitute decreases in the asset's intermediation costs. Thus, returns of costly assets are lower to force the household to take on a higher share of these assets. These opposing predictions allow me to test whether intermediaries indeed have higher risk expectations than households in the empirical exercise.

I test these predictions in the cross-section of monthly stock returns from 1990 to 2021. The empirical challenge is to find proxies for the cost of intermediation and the signal about the increasing wedge in risk expectation as defined in the model. Intermediation costs correlate positively with the FI's realized demand, as this measure inherently captures all potential reasons that prevent households from investing in certain assets. In contrast, simple transaction costs only reflect the direct costs of intermediation. Hence, I proxy the cost of intermediation with the institutional stock ownership from 13F files, which should be directly related to realized FI's demand. Second, I proxy the signal that widens the wedge in risk expectations with the residual of regressions of the VIX on realized variance. This residual captures (risk-neutral) expectations about future risk but is less related to asset-specific variance. I also test robustness with the VIX level and first differences, as the survey evidence suggests that the wedge in risk expectations is correlated with these measures. I adjust all of these measures to make them pro-cyclical, which aligns the cyclicality of the wedge in risk expectations in the model with the survey evidence. To test the model's main prediction, I use the proxies for intermediation costs and the risk wedge signal in panel regressions with 498,045 stock-month observations. I find that stock returns increase in institutional stock ownership when facing a positive risk wedge signal. Thus, this empirical result in the cross-section of stock returns aligns with the model's prediction when intermediaries have higher risk expectations than households, confirming the survey evidence.

Finally, I study the macroeconomic implications of the risk-return expectations of financial intermediaries. Recently, Maxted (Forthcoming) shows that in good times, high sentiment leads to excessively good expectations of the economy and, therefore, to a short-run amplification of investment. However, investors will be disappointed in the long run, triggering an investment boom-bust cycle. I construct artificial Sharpe ratios from the survey data to evaluate the short- and medium-term impact of expectations on the macroeconomy. Therefore, I estimate smooth local projections of various macroeconomic indicators on the expected Sharpe Ratios (Barnichon and Brownlees, 2019). Indeed, high Sharpe ratios lead to elevated industrial production, GDP, real investment, and real consumption for up to five quarters, but this effect turns negative in the medium term.

This paper relates to two strands in the literature. First, it adds to the recent studies that use survey data to learn about the actual expectations of return and risk.[2] For

[2] Adam and Nagel (2023) review the current literature on expectation data in asset pricing.

instance, Nagel and Xu (Forthcoming) study the dynamics of return expectations and find too low volatility compared to standard models. Similarly, De La O and Myers (2021) show that cash-flow expectations from analyst forecasts drive a significant part of the variation in the price-dividend ratio. Adam, Marcet, and Beutel (2017) show that capital gain expectations are strongly pro-cyclical, challenging standard predictions from rational expectation models. Lochstoer and Muir (2022) study risk expectations using the CFO Graham-Harvey survey and show that those are sticky, consistent with overextrapolation. Ben-David et al. (2013) find that CFOs severely underestimate the risk in the stock market. I add to this literature in three ways. First, I confirm the evidence on pro-cyclical nominal return expectations for FIs and non-FIs. Second, I do not find any evidence for differences in return expectations between FIs and non-FIs. Third, I show that both, FIs and non-FIs, severely underestimate the realized risk in the stock market; however, FIs are closer to the true value.

This paper also contributes to the intermediary asset pricing literature. Starting from the seminal papers of He and Krishnamurthy (2013) and Brunnermeier and Pedersen (2009), theoretical asset pricing models now include heterogeneity in the intermediary sector or biased beliefs (Kargar, 2021; Maxted, Forthcoming). Empirically, intermediaries matter for aggregate prices of various asset classes (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017; Haddad and Muir, 2021). Gruenthaler, Lorenz, and Meyerhof (2022) point out that higher-order moments in the financial sector are especially important for explaining the cross-section of asset returns. Recently, studies have shifted their focus toward the return expectations of institutional investors. Andonov and Rauh (2022) find evidence for extrapolative return expectations of public pension funds, while Dahlquist and Ibert (2023) find a counter-cyclical excess return premium for large asset managers. Dahlquist and Ibert (2023) choose the cyclically-adjusted price-earnings ratio as predictor variable to determine the cyclicality of return expectations. However, this predictor cannot reject non-stationarity in my sample period, while all other commonly used (and stationary) predictors do not confirm counter-cyclicality of return expectations. I contribute to this literature by distinguishing between FIs and non-FIs, directly comparing expectations on the same data set. More importantly, I focus not only on return but also risk expectations and document a substantial wedge in risk expectations of FIs and non-FIs. Third, I present a direct economic mechanism for how this wedge can affect stock returns and confirm it empirically.

The remainder of this paper is structured as follows. Section 2 presents the survey evidence. Section 3 introduces the asset pricing model and derives a testable prediction. Section 4 conducts the empirical analysis and analyzes the macroeconomic implications. Section 5 concludes.

2. Survey Evidence

2.1. Data and Variable Construction

I study the CFO Graham-Harvey survey to measure expectations of future returns and risks about the S&P 500 (see, e.g., Ben-David et al., 2013). Specifically, the quarterly survey asks US financial professionals ('CFOs') about their expectations of future macroeconomic and firm-specific outcomes.[3] The confidential survey microdata from Q4 2001 to Q4 2018 allows me to differentiate between the responses of CFOs of financial and non-financial firms. CFOs report the industry of their firm based on a predefined industry classification. One industry code includes the banking, finance, and insurance industry, while since 2015, it also includes the real estate industry. I use this industry classification to proxy 'financial CFOs,' while all other responses are attributed to the 'non-financial CFOs'. I discuss the validity of this assignment in Section 2.2.

I study the responses to the following survey questions: *During the next year, I expect the S&P 500 return will be* ('best guess return'), *there is a 1-in-10 chance the actual return will be less than* ('first decile return'), and *there is a 1-in-10 chance the actual return will be greater than* ('ninth decile return'). I follow the approach of the pollsters when

[3] The survey does not necessarily ask only CFOs but also financial professionals within the firm. I follow the naming of the survey and use the term 'CFO' interchangeably with 'financial professionals.'

Table 1: Descriptive Statistics

This table presents time-series summary statistics of the number of observations for non-financial CFOs (N) and financial CFOs (F) of the Graham-Harvey survey from Q4 2001 to Q4 2018. $\tilde{r}$ is the expected average return (%), $\tilde{q}_{0.9}$ is the expected ninth decile return, $\tilde{q}_{0.1}$ is the expected first decile return, and $\tilde{\sigma}$ is the difference between $\tilde{q}_{0.9}$ and $\tilde{q}_{0.1}$.

	Non-Fin.	Fin.	$\tilde{r}^N$	$\tilde{r}^F$	$\tilde{\sigma}^N$	$\tilde{\sigma}^F$	$\tilde{q}^N_{0.1}$	$\tilde{q}^F_{0.1}$	$\tilde{q}^N_{0.9}$	$\tilde{q}^F_{0.9}$
Mean	327.4	50.3	5.4	5.4	12.7	14.3	-2.1	-3.2	10.5	11.0
Median	336.0	51.0	5.5	5.3	12.3	13.9	-2.0	-3.2	10.3	11.0
Std.	105.6	19.6	1.3	1.5	2.1	2.3	1.9	2.2	1.6	1.7
Max.	666.0	101.0	9.2	9.8	19.2	19.8	1.6	2.0	14.8	15.3
Min.	130.0	13.0	2.0	2.3	9.6	10.4	-9.0	-8.9	6.8	7.5

reporting aggregate results and winsorize all responses at the 2.5% and 97.5% percentile to avoid relying on extreme outliers. For each of the three responses, I compute average values for financial and non-financial CFOs in each quarter. This results in a time series of expectations of financial and non-financial CFOs of the future one-year return $\tilde{r}$, the first decile return $\tilde{q}_{0.1}$, and the ninth decile return $\tilde{q}_{0.9}$. Following Lochstoer and Muir (2022), I also construct the difference between the ninth and first decile return for FIs and non-FIs, i.e., $\tilde{\sigma} = \tilde{q}_{0.9} - \tilde{q}_{0.1}$. This risk measure should be a multiple of expected volatility under the normality assumption.

Table 1 presents time-series summary statistics of the quarterly expectations distinguished by industry. On average, 340 non-financial CFOs and 52 financial CFOs participate in the survey at each point in time. Except for one survey in Q1 2002 with 13 observations, the survey always covers at least 19 financial CFOs for all three responses. The average nominal return expectations are 5.4% for both industries with a relatively low standard deviation of 1.3% and 1.5%. The risk measure for financial CFOs (14.3%) is higher than for non-financial CFOs (12.7%), which primarily comes from more pessimistic expected first decile returns (-3.2% vs. -2.1%). For the ninth decile return, financial CFOs, however, are more optimistic (11% vs. 10.5%). Overall, the summary statistics confirm that all four variables do not show extreme values after winsorization, and enough survey participants report valid responses.

To analyze the cyclicality of expectations in the following sections, I rely on different business cycle indicators following Nagel and Xu (Forthcoming). I use the log-consumption wealth ratio (Lettau and Ludvigson, 2001), the log price-dividend ratio from Robert Shiller's website, the long-run exponential average of past per-capita real aggregate dividend growth (Nagel and Xu, 2022), the net equity expansion of Welch and Goyal (2008), the one-year log growth of industrial production from FRED, the difference between the 10-year and 3-month treasury yield (TERM), the difference between Moody's Seasoned Baa and Aaa yield from FRED (DEF), the F1 factor of Ludvigson and Ng (2009), and the VIX. In addition, I add the intermediary risk factor of He et al. (2017) and the log cyclically adjusted price-earnings ratio from Robert Shiller's website. Dahlquist and Ibert (2023) find counter-cyclical CFO return expectations using the latter as a business cycle predictor. However, I test all predictors for stationarity in my sample period using an augmented Dickey-Fuller test, as non-stationarity in time-series regressions may lead to spurious results. Indeed, only six variables reject the null hypothesis of a unit root at the 5% level: the price-dividend ratio (PD), the log growth of industrial production (IP), the TERM and DEF spread, the F1 factor, and the VIX. I only include these variables in my analysis and make them comparable via two steps. First, I standardize all variables with their full sample standard deviation. Second, I take the negative values of PD and IP, as this makes all variables counter-cyclical, i.e., they have high values in bad times and low values in good times. Finally, I match the business cycle indicator to the survey data based on their last value in the month before the survey publication. This ensures that I do not use any forward-looking data in the analysis.

2.2. *Identifying Assumptions*

The CFO Graham-Harvey survey has been used in many studies to measure aggregate expectations and explain several economic phenomena (Nagel and Xu, Forthcoming; Lochstoer and Muir, 2022). I use the survey data to differentiate expectations between FIs and non-FIs at the micro-level, but this approach is subject to two identifying assumptions. First, I assume that CFOs report their true expectations about the future returns and risks of the S&P 500 and that there is no systemic misreporting. To test this, I replicate two well-known empirical facts from studies using different survey data with the CFO survey data. The intuition of this test is that a successful replication at least shows that the CFO survey is free of a specific misreporting issue compared to other surveys.

Specifically, I compare the return expectations of the semiannual Livingston survey with those from the CFO survey. The Livingston survey summarizes economists' expectations from various branches, including the government and academia. The left panel of Figure 1 confirms that both survey forecasts are positively correlated with a correlation coefficient of 0.56.[4] Second, I test the result of Giglio, Maggiori, Stroebel, and Utkus (2021) that disaster risk expectations are particularly high when return expectations are low. The right panel of Figure 1 shows a significant positive correlation for the first decile return forecasts and the average expected return with a correlation coefficient of 0.77. Higher disaster risk, i.e., more mass in the left tail of the probability distribution, is directly related to a lower first decile return. Thus, the positive correlation of the expected return with the first decile return is equivalent to a negative correlation with disaster risk. Thus, CFO survey forecasts align with previous research, and they predict internally consistent high downside risk when return expectations are low. I do not find any evidence of CFO-specific misreporting.

The crucial identifying assumption to differentiate between expectations of FIs and non-FIs concerns the self-reported industry classification of the CFOs. I assume that the survey responses of CFOs in the banking, finance, and insurance classification are *better* proxies for the expectations of the marginal FI than CFOs from industries like manufacturing, technology, or others. Importantly, CFOs from the finance industry do not need to be a perfect proxy for FI expectations as long as they are closer to the true value than CFOs from other industries because this paper focuses on *differences* between expectations. As survey data on marginal FI expectations are unavailable, I cannot em-

[4] In Figure A1 of the Online Appendix, I confirm this result using forecast data from Nagel and Xu (2022), where those forecasts are positively correlated with CFO forecasts.

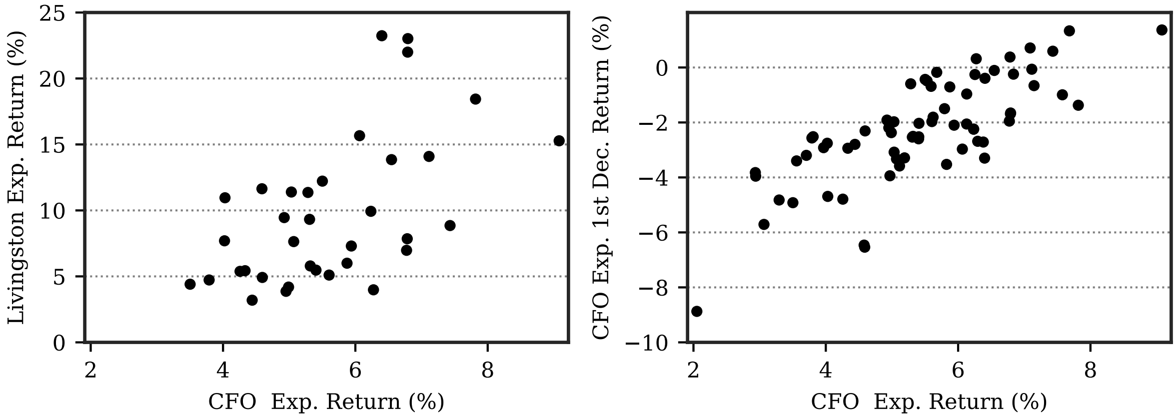

Fig. 1. Testing the Identifying Assumption

This figure plots the average nominal return expectations from the CFO Graham-Harvey survey against the average excess return forecasts of the Livingston survey (left) and the average CFO first decile return forecast (right).

pirically test this assumption. However, it is economically plausible that financial CFOs at least partially form their expectations based on information acquired within the firm. For financial CFOs, potential interlocutors are trading desks or research departments, possibly coming close to the marginal FI.

2.3. Return Expectations

I now analyze the subjective beliefs about the average future one-year return of FIs and non-FIs. The recent literature has studied return expectations extensively, especially for aggregate stock market indices like the S&P 500 (Adam and Nagel, 2023). However, these studies mainly focus on the cyclicality of return expectations, as common standard asset pricing models predict counter-cyclical return expectations. While this paper also analyzes the cyclicality, it focuses more on the differences in expectations of FIs and non-FIs. Further, I consider two return expectations: nominal and excess return expectations. The latter is calculated based on the assumption that survey participants know the current one-year treasury yield (Dahlquist and Ibert, 2023).

Figure 2 plots nominal and excess return expectations of FIs and non-FIs over time. In the upper panel, nominal return expectations are high in good times, with the highest

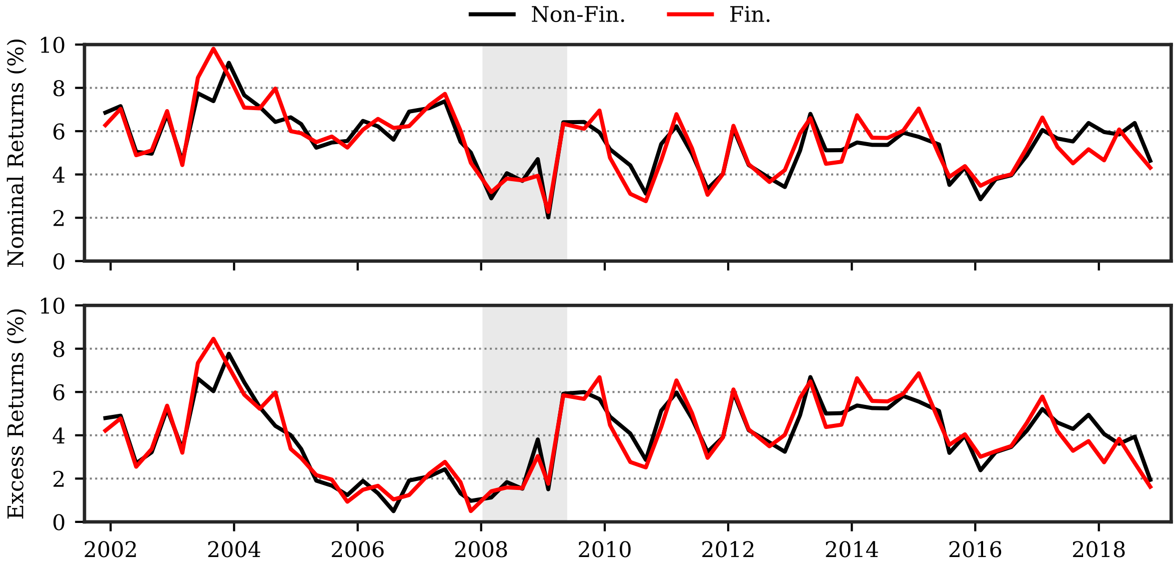

Fig. 2. Time Series of Return Expectations

This figure shows average nominal (upper panel) and excess (lower panel) return forecasts of financial (Fin.) and non-financial CFOs (Non-Fin.) over time. The grey-shaded area denotes NBER recessions.

expectations reaching 9.8% for non-FIs and 9.1% for FIs around the turn of the year 2004. Expected nominal returns of non-FIs and FIs are the lowest at the peak of the financial crisis in 2008 with 2.0% and 2.3%. Excess return expectations peaked around 2004 with 8.5% for FIs and 7.8% for non-FIs, but the lowest excess return expectations are less clear. Excess return expectations were low from 2006 onwards and started to rise in the late period of the financial crisis. Overall, the implications are twofold. First, nominal return expectations are pro-cyclical, while it is less clear for excess return expectations. However, the wedge between FIs and non-FIs is not substantial for both expectations.

To formally test the cyclicality of expectations, I run the following OLS regressions

$$\tilde{r}^i_t = \alpha^i + \beta^i_x x_t + \varepsilon_t, \tag{1}$$

where $\tilde{r}^i_t$ is current one-year forecasts of FIs and non-FIs, and x_t are standardized business cycle indicators, i.e., the negative PD ratio, the negative log industrial production growth (PD), the TERM and DEF spread, the F1 factor, or the VIX. Figure 3 plots the estimated betas β_x for FIs and non-FIs with the 95% confidence intervals estimated from Newey and West (1987) standard errors (two lags). Positive betas indicate counter-cyclicality of

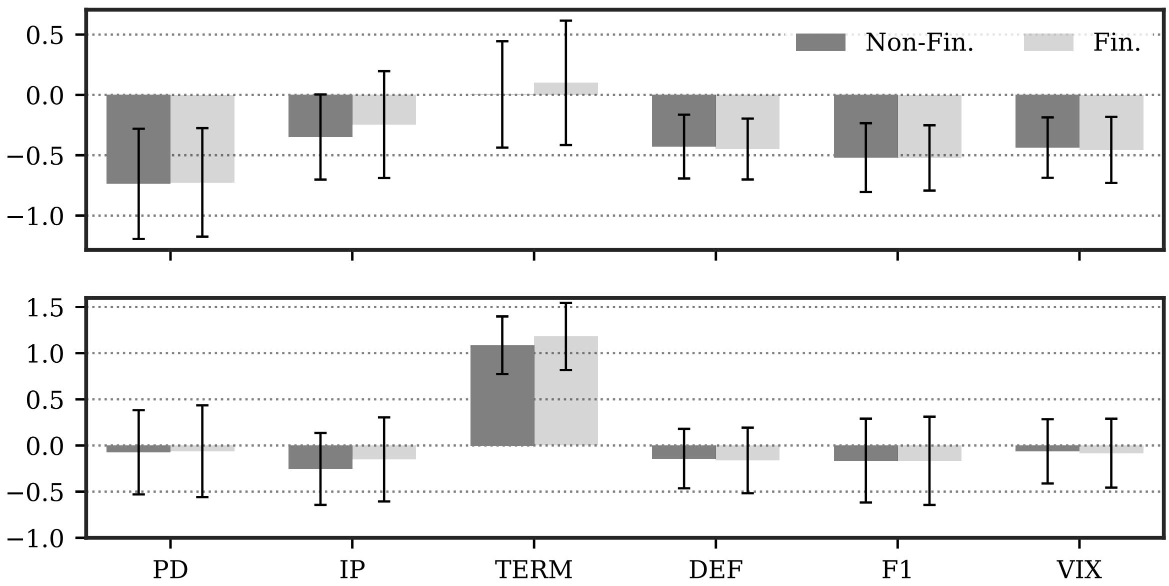

Fig. 3. Cyclicality of Return Expectations

This figure reports coefficients from regressions of financial (Fin.) and non-financial CFO (Non-Fin.) nominal (upper panel) and excess (lower panel) return expectations (in %) on standardized business cycle indicators. The bar denotes the coefficient, while the whiskers give the 95% confidence interval estimated using Newey and West (1987) standard errors (two lags). The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts.

the return expectations.

In the upper panel, the PD ratio, the DEF spread, the F1 factor, and the VIX significantly explain nominal return forecasts of FIs and non-FIs with a negative sign. IP is also significant at the 10% level for non-FIs, while the TERM spread is insignificant with a close to zero coefficient. However, the wedge between FI and non-FIs is small, suggesting no substantial time variation in the difference in expectations. In the lower panel, excess return expectations exhibit no time variation, as five out of six business cycle indicators are insignificant with economically small coefficients. Only the TERM spread is significant with a positive coefficient, indicating that it loads on the risk-free rate in the excess return expectations. The analysis indicates that nominal return expectations are pro-cyclical, while the risk-free rate is counter-cyclical, leading to statistically time-invariant excess return expectations. The wedge in return expectations, however, is small and negligible. In Table A1 of the Online Appendix, I run regressions of the differ-

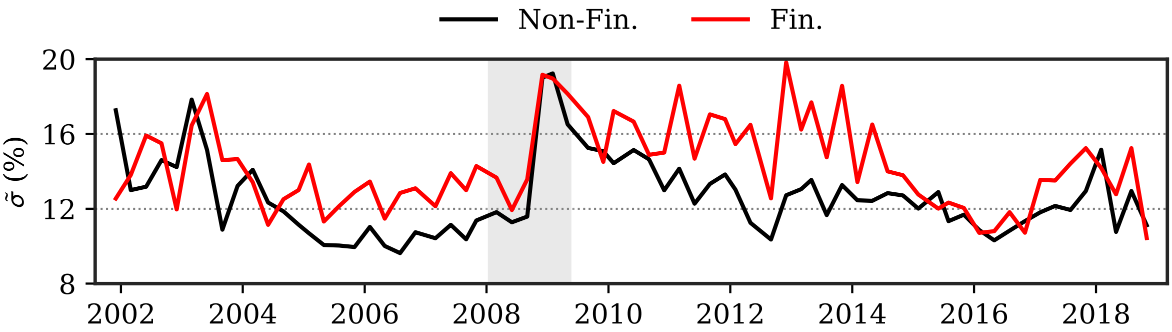

Fig. 4. Time Series of Risk Expectations

This figure shows average risk expectations of financial (Fin.) and non-financial CFOs (Non-Fin.) over time. Risk expectations are the difference between the expected first and ninth decile return. The grey-shaded area denotes NBER recessions.

ence in nominal return expectations ($\tilde{r}_t^F - \tilde{r}_t^N$) on the business cycle indicators as in (1). Neither the constant nor the time-varying wedge is significant in any of the specifications, confirming no substantial difference in return expectations of FIs and non-FIs.

2.4. *Risk Expectations*

I now turn to the risk expectations of FIs and non-FIs. Figure 4 presents the risk expectations over time, where risk expectations are the difference in the expected ninth and first decile return. Evidently, risk expectations of FIs are constantly higher than those of non-FIs, especially before and after the financial crisis. During bad times, however, the wedge narrows, with nearly the same values at the peak of the financial crisis and the Chinese stock market sell-off in 2015. In Figure A2 of the Online Appendix, I separately plot the time series of expected first and ninth decile returns. While both expectations for FIs and non-FIs share the same dynamics, the wedge is pre-dominant in the first decile return expectations, i.e., downside risk.

To test the cyclicality of risk expectations, I regress the risk expectations on the standardized business cycle indicators

$$\sigma_t^i = \alpha^i + \beta_x^i x_t + \varepsilon_t, \tag{2}$$

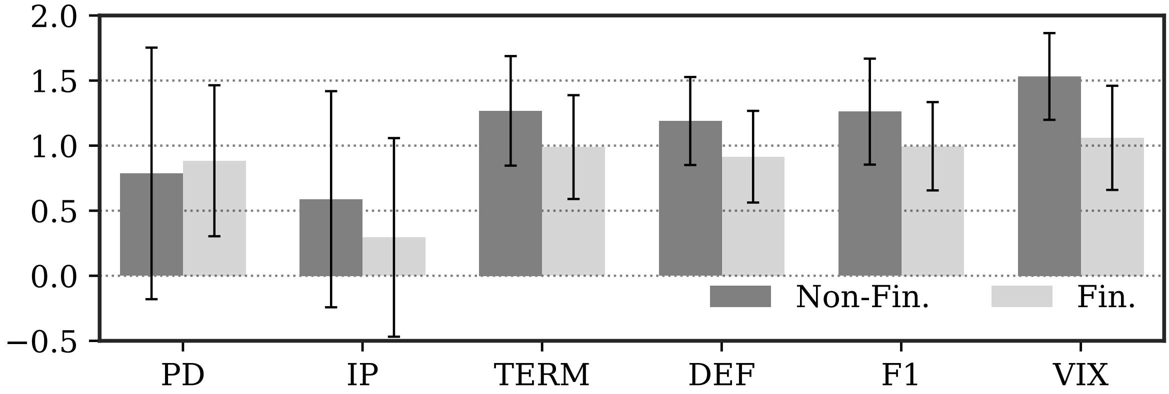

Fig. 5. Cyclicality of Risk Expectations

This figure reports coefficients from regressions of financial (Fin.) and non-financial CFO (Non-Fin.) risk expectations (in %) on standardized business cycle indicators. The bar denotes the coefficient, while the whiskers give the 95% confidence interval estimated using Newey and West (1987) standard errors (two lags). Risk expectations are the difference between the average expected ninth and first decile return. The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts.

where positive β^i_x indicate counter-cyclicality of risk expectations. Figure 5 plots the estimated betas with 95% confidence intervals from Newey and West (1987) standard errors (two lags). All six coefficients are positive, while five (four) coefficients for FI (non-FI) risk expectations are significant at the 5% level. Thus, risk expectations are counter-cyclical, with high values in bad times. Additionally, the wedge in risk expectations is substantial, with expectations of non-FIs reacting more strongly to business cycle variation. FI and non-FI risk expectations respond the strongest to variation in the VIX, which is not surprising as it also captures market expectations of future variance.

Finally, I test the differences in risk expectations, i.e., the risk wedge over the business cycle. Therefore, I run similar regressions as in (2) but replace the dependent variable with the risk wedge ($\tilde{\sigma}^F - \tilde{\sigma}^H$). Table 2 presents the estimated coefficients. FIs have a constantly higher risk expectation of 1.7 pp, which is highly significant across all specifications. The time variation of the risk wedge is pre-dominantly pro-cyclical, with negative coefficients for all business cycle indicators except the insignificant PD ratio coefficient. Three out of six coefficients are significant at the 10% level, while the other negative

Table 2: Regression of Risk Wedge on Business Cycle Predictors

This table reports coefficients from regressions of the difference of risk expectations (in %) of financial (Fin.) and non-financial CFOs (Non-Fin.) on standardized business cycle indicators. Risk expectations are the difference between the average expected ninth and first decile return. The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts. t-statistics are reported in parentheses and are estimated using Newey and West (1987) standard errors (two lags).

	$\tilde{\sigma}^F - \tilde{\sigma}^N$					
$x =$	PD	IP	TERM	DEF	F1	VIX
α	1.651***	1.651***	1.695***	1.651***	1.651***	1.651***
	(5.97)	(6.00)	(6.27)	(6.09)	(5.98)	(6.15)
x	0.097	−0.293*	−0.278	−0.274**	−0.266	−0.472***
	(0.30)	(−1.71)	(−1.55)	(−2.37)	(−1.56)	(−2.66)
Obs.	69	69	67	69	69	69
R^2	0.00	0.02	0.02	0.02	0.02	0.06

coefficients are borderline insignificant. I conclude that FIs constantly have higher risk expectations in the survey than non-FIs. However, this wedge narrows in bad times as non-FIs adjust their risk expectations more strongly.

In the Online Appendix, I test the cyclicality, and the constant differences in FI and non-FI expectations for the first and ninth decile returns separately. Figure A5 confirms that first decile returns are pro-cyclical, in line with the notion that first decile return expectations are inversely related to downside risk. Ninth decile returns are counter-cyclical but only significant for the VIX at the 5% level. In all specifications, I find a statistically highly significant negative wedge in first decile returns (Table A2) and a positive wedge in ninth decile returns (Table A3), where the former is almost twice as large as the latter. Thus, FIs perceive higher downside risks and upside potential compared to non-FIs. This leads to constantly lower FI expectations of future Sharpe Ratios due to elevated risk expectations (Table A4).

2.5. *Expected and Realized Risk*

Until now, this paper has focused on return and risk expectations and the difference between those for FIs and non-FIs. While there is no wedge in return expectations, I find evidence for substantial differences in risk expectations. Thus, the natural question arises what risk expectations are closer to the true risk in the market. For instance, Ben-David et al. (2013) show that CFOs severely underestimate the realized risk in the market. Ideally, I could compare the first and ninth decile return expectations with the conditional true probability distribution at each point in time. However, this conditional true probability distribution is generally not available, leading to a broad literature on estimating conditional physical probability distributions with certain assumptions (Cuesdeanu and Jackwerth, 2018). To avoid introducing further assumptions into the analysis, I use the unconditional probability distribution of historical realized returns.

The grey bar plots in Figure 6 show the distribution of the historical realized quarterly one-year S&P 500 returns from Q3 1963 to Q4 2018. The dashed black lines indicate the realized first decile return (-16.5%) and the ninth decile return (27.0%). In contrast, the average expected first decile returns are severely more optimistic, with -4.7% for FIs and -3.6% for non-FIs (left dashed red and blue lines). The expected ninth decile returns, however, are severely more pessimistic, with 9.5% for FIs and 9.0% for non-FIs (right dashed red and blue lines). I show in the Online Appendix in Figure A4 that the results are virtually unchanged when I use the realized historical distribution using the survey sample period from Q4 2001 to Q4 2018.

Thus, I confirm the finding of Ben-David et al. (2013) for FIs and non-FIs and find that they severely underestimate the true risk in the market. They expect less downside risk (higher expected first decile returns) and less upside potential (lower expected ninth decile returns). The difference between the ninth and first decile return is 14.32% for FIs and 12.67% for non-FIs, while the realized difference is 43.53%. Thus, risk expectations of FIs (non-FIs) are 67% (70%) lower than the historical realized average. Under the assumption of normally distributed returns, the volatility expectations of FIs and non-FIs are 5.6% and 4.9%, compared to the realized volatility of 17.0%. The difference between risk expectations of FIs and non-FIs seems small in light of the significantly higher actual risk in the market. However, this wedge in risk expectations is still economically and statistically highly significant, as FIs' risk expectations are 13% higher compared to non-

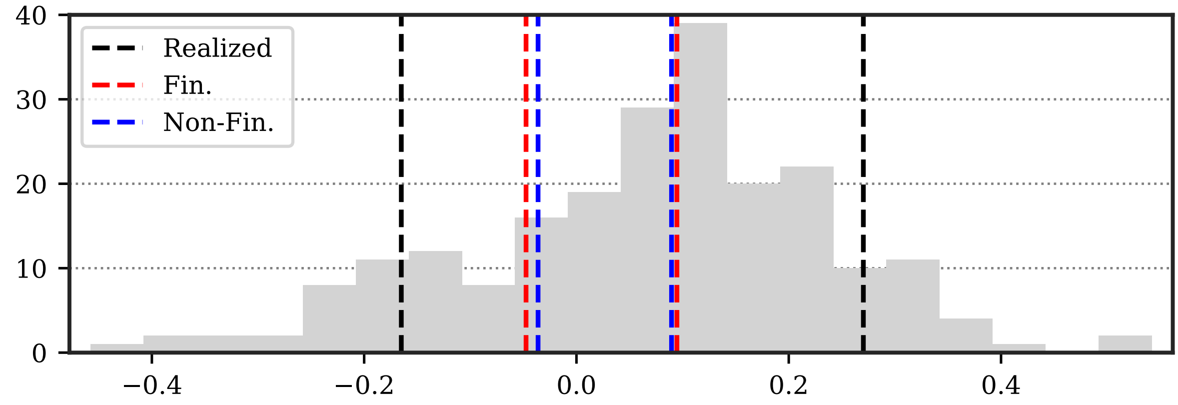

Fig. 6. Expected and Realized Return Distribution

This figure shows the expected and realized one-year return distribution. The grey barplots indicate the number of quarterly realized return observations from Q3 1963 to Q4 2018, where the black dashed lines indicate the first decile (left) and ninth decile return (right). The red dashed lines show the average expected first (left) and ninth (right) decile return of financial CFOs, while the blue dashed lines present the average expected first (left) and ninth (right) decile return of non-financial CFOs.

FIs risk expectations. This difference in risk expectations may affect assets differently in the cross-section based on their exposure to financial intermediaries.

3. Asset Pricing Model with Subjective Risk Beliefs

The survey evidence suggests that FIs have higher risk expectations than non-FIs for the aggregate market, but both agents severely underestimate the true risk. To test these facts in the cross-section of asset returns, I build on Haddad and Muir (2021) and use their model with a household and an intermediary sector with standard mean-variance preferences. I introduce subjective and potentially biased beliefs about asset-specific risks into the model. The model serves two purposes: first, it proposes a theoretical mechanism for how the wedge of risk expectations affects future asset returns. Second, it delivers an empirically testable prediction for the cross-section of asset returns.

3.1. Setup

The economy has two types of agents: the household and the financial sector. Both have standard mean-variance preferences with exponential utility and risk aversion parameters

γ_H and γ_I. There is one riskless asset and n risky assets with supply S. The payoffs of the risky assets are jointly normally distributed with mean μ and the positive definite variance-covariance matrix Σ. The agents invest in the assets at $t = 0$ and receive the payoffs at $t = 1$.

I introduce subjective and potentially biased risk beliefs into the model. The household and the financial intermediary do not necessarily agree on the true covariance-variance matrix Σ. Therefore, I assume that there is an exogenous signal Z that the household and intermediary receive and on which both build their risk expectations. Thus, the perceived household and financial intermediary covariance-variance matrices, i.e., Σ_H and Σ_I, are

$$\Sigma_H = (1 + \phi_H Z)\ \Sigma \tag{3}$$

$$\Sigma_I = (1 + \phi_I Z)\ \Sigma, \tag{4}$$

where Z is an exogenous aggregate signal that affects the expectation of the agents but not the actual idiosyncratic variance. To ensure that expected variances are always positive, I assume that $Z \in [0; 1]$, $\phi_H > -1$, and $\phi_I > -1$. ϕ_H and ϕ_I are the respective bias parameters of households and financial intermediaries. This modeling choice nests the model of Haddad and Muir (2021) as a special case, as agents have rational expectations when $\phi_H = \phi_I = 0$. Negative bias parameters indicate an underestimation of the true risk, while positive values would suggest an exaggeration.

The wedge in risk expectations between households and intermediaries is then

$$\Sigma_I - \Sigma_H = (\phi_I - \phi_H) Z\ \Sigma. \tag{5}$$

Therefore, the sign of the wedge solely depends on the difference of the bias parameters ϕ_I and ϕ_H, while the exogenous shock Z and the true variance-covariance matrix Σ determine the size. Hence, Z can be interpreted as a 'risk wedge shock', as it increases (decreases) the difference in risk expectations between the intermediary and household for high (low) values. Further, the modeling choice cannot differentiate between the cases when both agents are rational ($\phi_I = \phi_H = 0$) and similarly biased ($\phi_I = \phi_H \neq 0$). However, I aim to test the *relation* of the biases of households and intermediaries; in other words, whether financial intermediaries have higher risk expectations than households. In that case, the model has two advantages: first, it makes opposing predictions for the cross-section of asset returns when intermediaries have higher (lower) risk expectations, that is, $\phi_I > (<)\ \phi_H$. These opposing predictions allow me to verify only one in the empirical exercise and thus provide evidence for the relation of risk expectations of intermediaries compared to households. Second, assuming an overall exogenous risk wedge signal Z keeps the model as parsimonious as possible without the need to model a multi-period economy. Thus, I do not need to assume a process for the wedge in risk expectations.

The household can either invest directly in each asset or through the intermediary. However, when trading directly in the risky asset, they face quadratic costs increasing in the underlying asset's perceived risk. For instance, Eisfeldt, Lustig, and Zhang (Forthcoming) show that non-sophisticated investors participate less in complex asset markets with high idiosyncratic volatility, as they do not have adequate pricing models. In line with this, Haddad and Muir (2021) argue that these costs capture intermediation costs and other reasons for the households' unwillingness to invest in certain assets. In matrix notation, the costs of trading in the asset universe are thus $\frac{1}{2}D'_H \Sigma_{diag,H} C D_H$, where D_H is the demand vector of households for the risky assets, and C is a diagonal matrix with the intermediation costs on the diagonal. Instead of investing directly into the assets, the household can invest costlessly through the financial intermediary that it owns. However, the household does not control the investment decisions of the intermediary. This comes from the fact that the intermediary faces constraints that affect their investment decisions, e.g., equity or debt constraints (He and Krishnamurthy, 2013; Adrian and Shin, 2014; Brunnermeier and Sannikov, 2014) or different risk attitudes (Kargar, 2021).[5]

This setup of the economy leads to two different optimization problems. The interme-

[5]See Internet Appendix I.D of Haddad and Muir (2021) for an in-depth discussion of the assumptions of separate investment decisions and the intermediation costs increasing in an asset's idiosyncratic risk.

diary optimizes separately from the household sector, that is,

$$\max_{D_I} D_I'(\mu - \rho) - \frac{\gamma_I}{2} D_I' \Sigma_I D_I, \tag{6}$$

where $\mu - \rho$ is the expected return with equilibrium price vector ρ.[6] The intermediary passes through its payoffs to the household sector, which takes the demand of the intermediary sector as exogenous and optimizes accordingly

$$\max_{D_H} (D_H + D_I)'(\mu - \rho) - \frac{\gamma_H}{2}(D_H + D_I)' \Sigma_H (D_H + D_I) - \frac{1}{2} D_H' \Sigma_{diag,H} C D_H. \tag{7}$$

The first two terms of the household optimization are equivalent to the intermediary optimization but additionally consider the intermediary demand. Finally, the last term represents the intermediation costs when investing directly in risky assets. Note that (6) and (7) both include the subjective beliefs about the true covariance-variance matrix.

3.2. Solution

I solve the model for the expected return of the risky assets.[7] The optimal demand of the financial intermediary is

$$D_I^* = \frac{1}{\gamma_I} \Sigma_I^{-1} (\mu - \rho), \tag{8}$$

while the optimal demand of the household is

$$D_H^* = (\gamma_H \Sigma_H + \Sigma_{diag,H} C)^{-1} (\mu - \rho) - (\gamma_H \Sigma_H + \Sigma_{diag,H} C)^{-1} \gamma_H \Sigma_H D_I. \tag{9}$$

The financial intermediary invests in its subjective mean-variance efficient portfolio. However, the household also considers that it holds other assets through the intermediary represented in the last term of (9). One necessary assumption in this setup is that $(1 + \phi_I Z)\gamma_I > (1 + \phi_H Z)\gamma_H$ because otherwise, the households would hold all risky assets

[6] In fact, $\mu - \rho$ is the expected gain, but I follow the naming convention of Haddad and Muir (2021) and denote it as 'expected return.'

[7] Proofs of the following results are derived in Section B of the Online Appendix.

directly through the intermediary ($D_I^* \leq 0$). Empirically, households have direct holdings of risky assets and exert demand pressure affecting asset prices (Koijen and Yogo, 2019), validating this assumption. This assumption does not necessarily violate the common assumption in intermediary asset pricing models where the *relative* risk aversion of intermediaries is lower than those of households. These two assumptions can coexist if the intermediary sector is not too large, as intermediaries' relative risk aversion scales with its wealth (Haddad and Muir, 2021).

Market clearing $S = D_I^* + D_H^*$ then implies

$$\begin{aligned}(\mu - \rho) =& \Sigma\Big[\Sigma(\gamma_H \Sigma + \Sigma_{diag} C)^{-1}(1 + \phi_H Z)^{-1} \\ &+ \frac{1}{\gamma_I}\Sigma_{diag} C(\gamma_H \Sigma + \Sigma_{diag} C)^{-1}(1 + \phi_I Z)^{-1}\Big]^{-1} S. \end{aligned} \tag{10}$$

This expression is the general solution for the expected return, and it composes two different distortions compared to the case when no financial frictions are present. If $\phi_I = \phi_H = 0$ and $C > 0$, the second term in (10) accounts for the fact that intermediaries affect asset prices when financial frictions are present, even if all agents have rational beliefs (Haddad and Muir, 2021). However, I focus on the distortions introduced by the biased risk beliefs. These are twofold: first, even in a world without financial frictions but with a household with biased risk beliefs, the equilibrium changes to $\mu - \rho = \gamma_H \Sigma(1 + \phi_H Z)S$. The subjective variance expectations change the household's investment decision and, therefore, the asset's expected return. The variance expectations of the intermediary sector only affect the asset's expected return if financial frictions are present. Then, intermediaries' risk beliefs operate through $(1 + \phi_I Z)^{-1}$ in the second term of (10).

The solution of (10) nests the expected return in the model of Haddad and Muir (2021) as a special case, where all agents have rational expectations ($\phi_H = \phi_I = 0$). In their model, the elasticity of the risk premium to intermediary risk aversion increases in intermediation costs, while the opposite is true for households' risk aversion. They empirically confirm these predictions using empirical risk aversion measures of the intermediary sector (Adrian et al., 2014; He et al., 2017) and households (Campbell and Cochrane, 1999;

Lettau and Ludvigson, 2001). I study these two main predictions in my model in the Online Appendix in Section B.3 when biased risk beliefs are present. I find that the return elasticity with respect to household risk aversion is unchanged compared to Haddad and Muir (2021). Additionally, the return elasticity with respect to intermediary risk aversion only changes in the effect size, but the overall sign remains unchanged. Thus, the main result of Haddad and Muir (2021) also holds in my model with potentially biased risk beliefs, regardless of the sign of bias in risk expectations.

3.3. Main Prediction

I now derive the model's main prediction for the cross-section of asset returns. To obtain closed-form solutions, I assume that $\Sigma = \Sigma_{diag}$ and the supply of asset i is one. Thus, the expected return of asset i is

$$\mu_i - \rho_i = \frac{\gamma_H + c_i}{(1+\phi_H z)^{-1} + (1+\phi_I z)^{-1}\frac{c_i}{\gamma_I}}\sigma_i^2. \tag{11}$$

The subjective biases of intermediaries and households affect the expected return of asset i through two channels: through the biased risk beliefs of the households and through the intermediaries' beliefs when financial frictions are present. First, I study the case when no financial frictions are present ($c_i = 0$). Then, the elasticity of substitution of the demand of the intermediary and the household for the risky asset is one, as the household does not face any costs in investing in the risky asset directly, making the intermediary a 'veil.' Specifically, even if the intermediary has higher risk beliefs than the household and thus has a lower demand for the risky asset in (8), the household offsets the lower FI demand with higher demand in (9), as he is indifferent between holding the asset directly or via the intermediary. Only when the subjective mean-variance optimal portfolio of the household changes due to shocks in $\phi_H z$, the expected returns adjust to clear the market. For instance, for positive z-shocks and $\phi_H > 0$ ($\phi_H < 0$), households overestimate (underestimate) the true risk in the market, triggering a negative (positive) demand pressure on the risky asset and increase (decrease) expected returns.

In the scenario without financial frictions, the return sensitivity to z-shocks only depends on the biased risk beliefs of the household. However, when the intermediary has biased risk expectations *and* financial frictions are present, the expected return also depends on the risk beliefs of the intermediary. Assume that both agents overestimate the true risk in the market ($\phi_I > 0$ and $\phi_H > 0$). A positive z-shock leads to overestimating risks for both agents, inducing negative demand pressure from the intermediary and the household through (8) and (9). However, the intermediary or the household need to take a higher demand share to clear the market; therefore, the expected return rises. The same mechanism applies when both agents underestimate the risk in the market, resulting in lower expected returns as both agents wish to increase their positions in the risky asset. However, if one agent overestimates while the other underestimates the risk in the market, the sign of the return sensitivity to z-shocks is less clear. In that case, it depends not only on the bias parameters ϕ_H and ϕ_I but also on the intermediation costs c and the intermediaries' risk aversion γ_I.

This result affects the whole cross-section of assets. However, the magnitude of the return sensitivity also depends on the asset-specific cost of intermediation. To formalize this, I take the second derivative of the standardized expected return with respect to the risk wedge signal z and the cost of intermediation c that is

$$\frac{\frac{1}{\mu_i-\rho_i}\frac{\partial \mu}{\partial z}}{\partial c} = (\phi_I - \phi_H)\frac{\gamma_I}{(c_i(1+\phi_H z_i) + \gamma_I(1+\phi_I z_i))^2}. \tag{12}$$

The standardized return sensitivity to a z-shock is increasing (decreasing) in the cost of intermediation when intermediaries have higher (lower) risk expectations than the household. (12) gives a prediction about the return sensitivity to z-shocks for the cross-section of asset returns. I follow Haddad and Muir (2021) and standardize the return sensitivity to z-shocks with the average expected return. This standardization accounts for the fact that assets with absolute higher risk premia or higher supply mechanically move more with changes in the risk beliefs.

The intuition of this prediction follows from the fact that households dislike holding

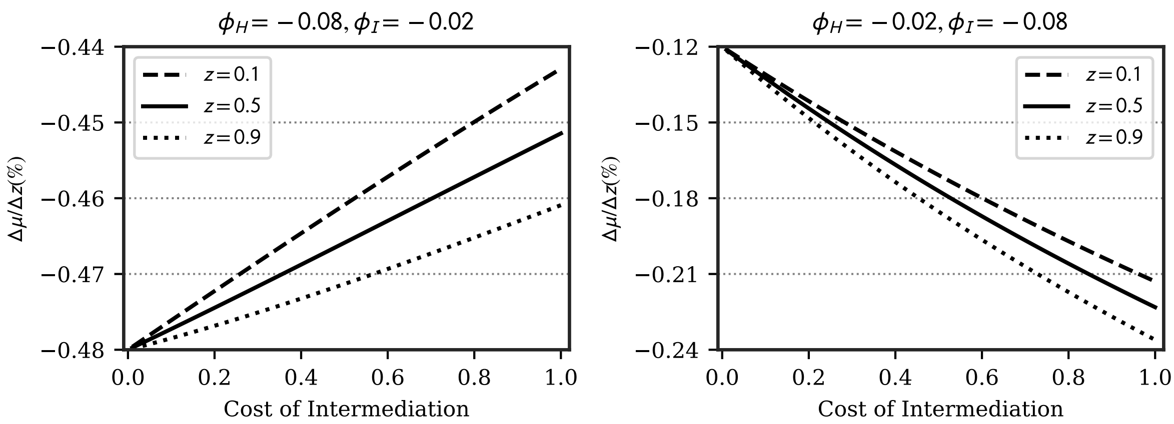

Fig. 7. Return Sensitivity conditional on Risk Expectations Wedge

This figure plots the sensitivity of the expected return of an asset with respect to the exogenous shock z ($\frac{\Delta\mu}{\Delta z}$) against the costs of intermediating the asset. The left panel shows the sensitivity when risk expectations of intermediaries (ϕ_I) are higher than for households (ϕ_H), while the right panel shows the opposite case. In both panels, the model parameters are $\gamma_I = 4$, $\gamma_H = 3$, and $\sigma^2 = 0.02$.

risky assets directly, as they can own these assets costlessly through the intermediary. If intermediaries have higher risk expectations than households, intermediaries' optimal demand in (8) is relatively low when the wedge in risk expectations widens. The household appreciates holding assets with low intermediation costs, so the intermediary increases its share in costly assets in equilibrium. Accordingly, the expected returns are higher for assets with high intermediation costs when facing a positive risk wedge shock. Vice versa, if the risk expectations of the intermediary are lower than the household, the intermediary demand is relatively high. To clear the market, the returns of assets with high intermediation costs are lower, forcing the household to take a larger share of these assets.

I simulate the model with risk aversion parameters $\gamma_I = 4$ and $\gamma_H = 3$, and an asset with variance $\sigma^2 = 0.02$. Figure 7 plots the model's main prediction, that is, the return sensitivity with respect to z-shocks against the different values for the cost of intermediation. The left plot shows when intermediaries have higher risk expectations than households ($\phi_I = -0.02, \phi_H = -0.08$), while the right plot presents the opposite case ($\phi_I = -0.08, \phi_H = -0.02$). As predicted by (12), the return sensitivity increases for higher intermediary risk expectations while decreasing for lower risk expectations. The initial value of z only slightly affects the effect size but does not influence the overall result.

4. Empirical Analysis

In this section, I empirically test the prediction from the asset pricing model in Section 3. The model predicts that if intermediaries have higher risk expectations than households, the return sensitivity of an asset should increase in the cost of intermediation when the wedge in risk expectations widens. Finally, I also study the macroeconomic implications of the empirical wedge in subjective risk and return expectations.

4.1. Data and Empirical Approach

I use monthly CRSP stock data from 1990 to 2021 and apply standard cross-sectional asset pricing filters. Specifically, I only include stocks with share codes 10 and 11, and those that trade on the NYSE, AMEX, and NASDAQ (exchange codes 1, 2, 3, 31, 32, 33). Moreover, I exclude stocks in the financial industry (SIC code between 6000 and 6999). To exclude microcaps, I only use stocks with prices higher than 5$ and those with a market capitalization higher than the first NYSE quintile (Gonçalves, 2021). Finally, each stock must be available for at least three years, ensuring that firm-fixed effects in panel regressions are estimated based on sufficient sample size.

According to (12), the model's main prediction relates the return sensitivity to a signal about the wedge in risk expectations and the cost of intermediation. Therefore, I estimate the following OLS panel regressions

$$\frac{r^i_{t+1} - r^i_t}{\sigma^i} = \alpha_i + \gamma_t + \beta(z_t \times c^i_t) + \psi c^i_t + \eta Controls^i_t + \epsilon_t, \tag{13}$$

where the left-hand side is the one-month ahead realized Sharpe Ratio of the stock i. As noted in Section 3, the scaling of the realized returns is useful in terms of comparability across different stocks. Ideally, I would use the unconditional risk premium for each stock as a scaling measure, but these are difficult to estimate, especially for short samples. Hence, I follow Haddad and Muir (2021) and normalize the realized return with the idiosyncratic volatility of each stock. I include month-fixed effects γ_t in each specification to account for time-variant but aggregate shocks, which may affect the realized Sharpe ratio. γ_t captures the aggregate effect of z_t on the Sharpe Ratio, so I do not include it individually in (13). Additionally, I include in some specifications firm-fixed effects α_i to account for time-invariant but constant differences across entities. Finally, to control for time-varying differences across entities unrelated to the cost of intermediation, I also include Fama and French (2015) five-factor betas estimated from 252-day rolling window regressions ($Controls_t^i$).

The estimated coefficient β from the interaction term $z_t \times c_t^i$ in (13) corresponds directly to (12). Therefore, the sign of β constitutes the central element of the model-implied test to differentiate between the risk expectations of intermediaries and households. If the return sensitivity to the risk wedge signal is increasing in the costs of intermediation ($\beta > 0$), then this provides evidence for intermediaries having higher risk expectations than households. Vice versa, if the sensitivity decreases in the intermediation costs ($\beta < 0$), this would induce lower intermediary risk beliefs than households.

However, the empirical challenge is finding proxies for the aggregate signal (z_t) and the asset-specific intermediation costs (c_t^i). The former should meet two conditions. First, it should be an *aggregate* forward-looking signal that only affects the risk expectations of households and intermediaries but not the actual idiosyncratic risk of the assets. Additionally, risk expectations are sticky, and, therefore, realized volatilities do not account for this fact (Lochstoer and Muir, 2022). Second, the risk wedge signal should be pro-cyclical. The model-implied wedge in risk expectations,

$$(\sigma_i^I)^2 - (\sigma_i^H)^2 = (\phi_I - \phi_H)\ z\ \sigma_i^2, \tag{14}$$

is directly related to the level of the signal z. Regardless of the relation of ϕ_I and ϕ_H, low values of z imply a low wedge in expectations for $z \in [0, 1]$. Since the survey evidence suggests a pro-cyclical wedge, z must also be pro-cyclical. However, all commonly used risk measures are naturally counter-cyclical, so I use *negative* values for the empirical analysis to make them pro-cyclical. First, I estimate the residual from regressions of the VIX level on the realized volatility, where the latter is estimated from squared daily returns within a month. This residual ε_t should incorporate (risk-neutral) expectations about future risk unrelated to the current level of realized volatility.[8] This variable is the most suitable proxy for z, as it captures risk expectations but is less related to asset-specific variance σ_i^2 in (14). I also test the level and first differences of the *negative* VIX. As shown in Section 2, the VIX is negatively correlated to the wedge in risk expectations, indicating that it should at least partially capture the dynamics of z. However, these variables are related to the asset-specific variance σ_i^2 (14), although the firm-fixed and time-fixed effects in (13) should reduce this effect.

Second, I motivate the choice of the empirical proxy of c_t^i directly from the model, as the demand of the intermediary relative to the household demand is given by

$$\frac{D_I}{D_H} = \frac{c_i + \gamma_H}{\gamma_I \frac{1+\phi_I z}{1+\phi_H z} - \gamma_H}. \tag{15}$$

Thus, the realized demand of the intermediary is positively related to the cost of intermediation. As discussed in Section 3, the intermediation costs comprise not only trading costs but all possible factors that might decrease households' willingness to invest in certain assets. Hence, actual trading costs as an empirical proxy of c_t^i only capture a subset of potential reasons why households do not invest. In contrast, the realized demand of intermediaries inherently captures all factors that prevent households from investing. Accordingly, I use the Thomson Reuters institutional stock ownership data from 13-F filings as an empirical proxy for the realized demand of the intermediary and, therefore, for intermediation costs c_t^i. I aggregate the data to obtain each stock's quarterly share

[8] The residual captures forward-looking expectations and variance risk premia unrelated to realized volatility. I regress the wedge in risk expectations from the survey data on the standardized squared variance risk premium estimate of Bekaert and Hoerova (2014) and find that they are significantly negatively related ($\beta = -0.572$, $t = -3.26$), similar to the VIX in Table 2 ($\beta = -0.472$, $t = -2.66$). Thus, the residual still correlates with the wedge in risk expectations, whether due to variance risk premia or risk expectations.

Table 3: Panel Regressions of One-Month Ahead Sharpe Ratios

This table reports coefficients from panel regressions of one-month ahead Sharpe Ratios on institutional stock ownership and its interaction with different risk wedge signals. Risk wedge signals include the negative level (VIX) and first-differences (ΔVIX) of the VIX as well as the negative residual of the regression of the VIX on realized volatility (ε). Institutional stock ownership (IO) is cross-sectionally standardized. Control variables include the betas from 252-day rolling window regressions on the Fama and French (2015) five factors. The sample period is from February 1990 to June 2021. t-statistics are reported in parentheses and are computed using standard errors clustered at the firm and monthly level.

	$SR_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$-\varepsilon_t \times IO_{i,t}$	0.192***	0.204***				
	(2.95)	(3.10)				
$-VIX_t \times IO_{i,t}$			0.130***	0.136***		
			(3.15)	(3.21)		
$-\Delta VIX_t \times IO_{i,t}$					0.180***	0.179***
					(2.64)	(2.62)
$IO_{i,t}$	−1.794***	−5.103***	0.745	−2.434***	−1.788***	−5.093***
	(−6.21)	(−10.07)	(0.99)	(−2.89)	(−6.15)	(−9.92)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes
Obs.	498045	498045	498045	498045	498045	498045
Within R^2	0.18	0.25	0.17	0.24	0.17	0.24

of institutional stock ownership. Finally, I cross-sectionally standardize this variable to account for a potential time trend in institutional stock ownership.

4.2. Testing the Prediction

Empirically, I estimate the following OLS panel regressions

$$\frac{r^i_{t+1} - r^i_t}{\sigma^i} = \hat{\alpha}_i + \hat{\gamma}_t + \hat{\beta}(x_t \times IO^i_t) + \hat{\psi} IO^i_t + \hat{\eta} Controls^i_t + \hat{\epsilon}_t, \tag{16}$$

where $x_t \in \{-\varepsilon_t, -VIX_t, -\Delta VIX_t\}$ is one of the proxies for the wedge in risk expectations and IO^i_t is the cross-sectionally standardized institutional ownership share. Table 3 reports regression coefficients $\hat{\beta}$ and $\hat{\psi}$, while t-statistics are reported in parentheses. Standard errors are clustered at the firm- and monthly-level to account for cross-correlations within months and firms. In each specification, I include month-fixed effects and the control variables, while in all even column numbers, I add firm-fixed effects as well.

Across all model specifications, the interaction terms of the respective risk wedge signal with the institutional ownership are positive and highly significant at the 1% confidence level. For example, considering two stocks with a cross-sectional difference of one standard deviation in institutional stock ownership, a one-percentage point shock to the risk wedge signal leads to a higher Sharpe Ratio of 0.204 pp for the residual (column 2), 0.136 pp for the level of VIX (column 4), and 0.179 pp for differences in the VIX (column 6) for the more intermediated stock. The results are virtually unchanged when excluding firm-fixed effects, with only slightly lower estimates for columns (1) and (3). The $IO_{i,t}$ estimate is significant and negative for all specifications except column (3) when including the negative VIX and no firm-fixed effects. However, these results do not affect the coefficient of the interaction term.

The analysis aligns with the model's prediction in (12) that the return sensitivity to an increasing wedge between intermediary and household risk expectations increases in the intermediation costs of the asset. This result supports the survey evidence, that is, that intermediaries constantly have higher risk expectations than households.

4.3. Macroeconomic Implications

Differences in subjective expectations may also have severe macroeconomic implications. For instance, Maxted (Forthcoming) shows that an intermediary asset pricing model where agents have biased expectations about log capital growth results in a sentiment-driven investment boom-bust cycle. Elevated sentiment in good economic times induces a short-run amplification, where investment and output rise more than in rational expectation models. However, intermediaries are disappointed in the long run, so the effect reverses. The psychological effect of over-optimism in good times and over-pessimism in bad times may also apply to subjective expectations about the stock market and thus may co-move with the investment boom-bust cycle.

I use Sharpe Ratio expectations from the CFO survey data to test the macroeconomic implications of subjective expectations of financial intermediaries. I follow Grigoris and

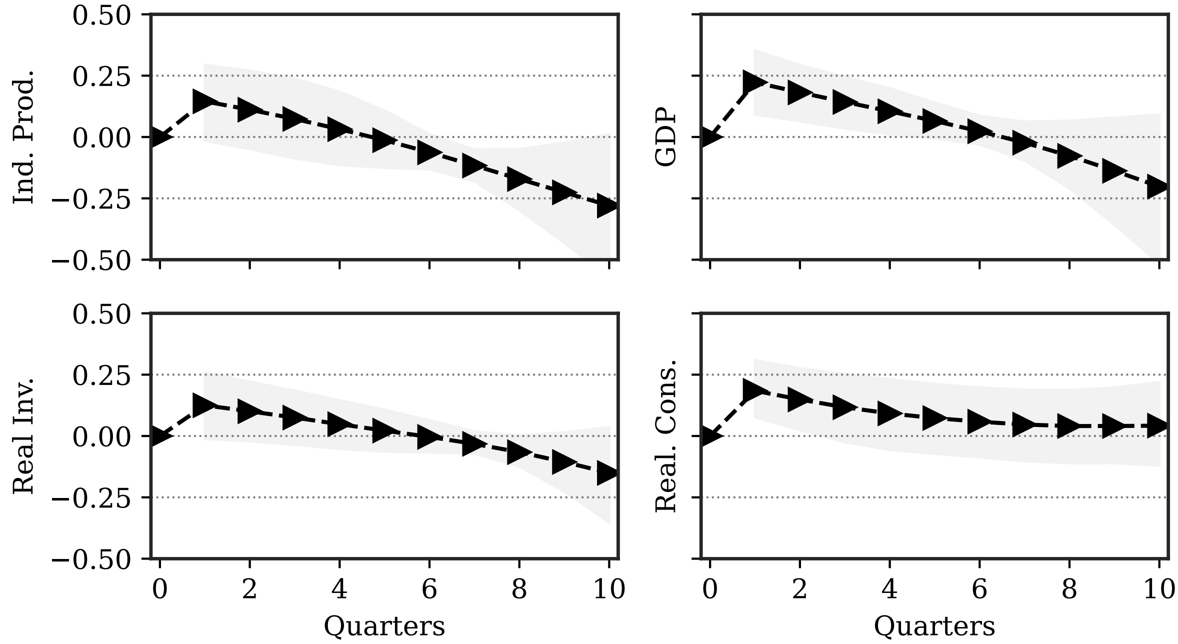

Fig. 8. Smooth Local Projections on Expected Sharpe Ratios

This figure shows coefficients from smooth local projections (Barnichon and Brownlees, 2019) of industrial production, GDP, real investment, and real consumption on financial CFOs' expected Sharpe ratios. Control variables are the lagged expected Sharpe ratio, the contemporaneous and lagged independent variable, the lagged market return, the lagged TERM and DEF spread, and the lagged inflation rate. The grey-shaded area denotes the bootstrapped 90%-confidence interval.

Segal (2023) and estimate smooth local projections (Barnichon and Brownlees, 2019),

$$y_{t+h} = \beta_{0,h} + \beta_{1,h} y_t + \beta_{2,h} \hat{SR}_t^F + \gamma_{1,h} Controls_{t-1} + \varepsilon_{t+h}, \tag{17}$$

where y_{t+h} are the corresponding future macroeconomic variables, $\hat{SR}_t^F$ is the subjective Sharpe Ratio estimated from survey data, and $Controls$ includes various control variables.[9] The macroeconomic variables are standardized and include the log growth in industrial production, real consumption, real investment, and real GDP as defined in Grigoris and Segal (2023). The control variables include the contemporaneous and lagged independent variable, the lagged market return, the lagged TERM and DEF spread, and the lagged inflation rate.

[9]Specifically, the subjective Sharpe Ratio is derived under the normality assumption and equals

$$\hat{SR}_t^F = \frac{\tilde{r}_t^F - rf_t}{\frac{1}{2.56}\tilde{\sigma}_t^F}. \tag{18}$$

Figure 8 presents the estimated impulse response functions and 90% confidence intervals estimated from bootstrapped standard errors.[10] The underlying identification assumes that a shock to subjective expectations does not immediately affect the macroeconomic variables. In that case, GDP and real consumption rise for the first two to five quarters, while the effect is similar for industrial production and real investment but statistically less evident. However, for all macro variables except real consumption, there is a long-run reversal around eight quarters after the shock. Subjective expectations also seem to induce a boom-bust cycle, in line with predictions from Maxted (Forthcoming). However, the main difference is that Maxted (Forthcoming) studies subjective expectations about log capital growth, while here, survey responses state expectations about future risks and returns. Thus, the natural question arises of how these two expectations are intertwined and what drives the boom-bust cycle. I leave further analysis of the macroeconomic implications of subjective asset pricing expectations to future research, especially as this requires a richer data set that spans a longer time period.

5. Conclusion

Expectations of financial intermediaries are crucial in explaining the cross-section of asset returns. I study the risk and return expectations of intermediaries and non-intermediaries using the CFO Graham-Harvey survey. Return expectations are similar, while risk expectations of intermediaries are constantly higher. However, both significantly underestimate the true risk in the market. I test the implications of the survey evidence in an intermediary asset pricing model and show how the wedge of subjective expectations of intermediaries and households affects the cross-section of asset returns. If intermediaries have higher risk expectations than households, highly intermediated assets earn higher returns than less intermediated assets when the wedge in risk expectations widens. I provide empirical evidence supporting this prediction in panel regressions with 498,045 stock-month observations.

[10] I thankfully rely on the MATLAB code provided by Barnichon and Brownlees (2019).

I find that differences in risk expectations of intermediaries and non-intermediaries significantly affect the cross-section of stock returns. Accordingly, Gruenthaler et al. (2022) show that a proxy for intermediaries' health incorporating higher-order moments better explains the cross-section of asset returns. Thus, analyzing subjective expectations of higher-order moments may be a fruitful avenue for future research. Additionally, this paper provides evidence that intermediaries also depart from the rational expectations paradigm. Consequently, future research must incorporate intermediaries' subjective expectations into equilibrium intermediary asset pricing models. Maxted (Forthcoming) has taken a first step in this direction, assuming sentiment-driven expectations about the capital stock. However, this modeling approach does not necessarily imply subjective risk and return expectations aligning well with the survey data. Thus, future research needs to disentangle the different expectations from one another and study through which economic mechanism they affect asset prices.

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Online Appendix

Risk-Return Expectations of Financial Intermediaries

Table of Contents:

Appendix A. Additional Figures and Tables

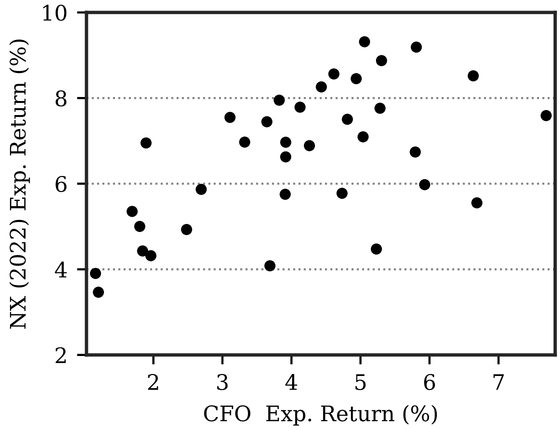

Fig. A1. Testing the Identifying Assumption

This figure plots the average expected excess return from the CFO Graham-Harvey survey against the average excess return forecasts constructed in Nagel and Xu (2022).

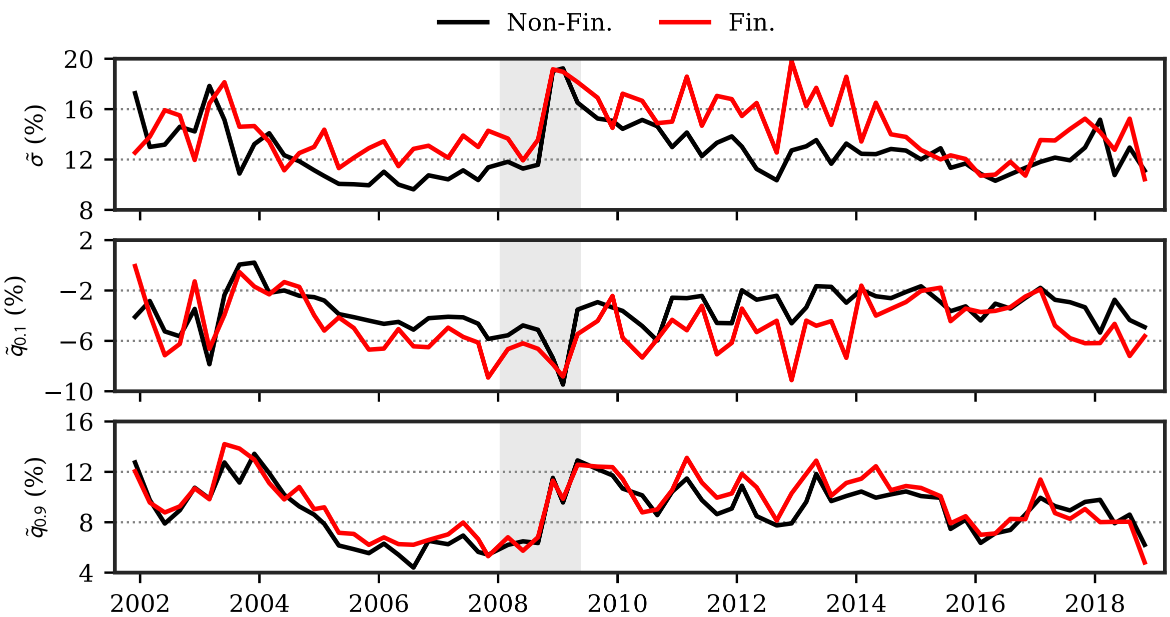

Fig. A2. Time Series of Risk Expectations

This figure shows average risk (upper panel), first decile excess return (middle panel), and ninth decile excess return expectations of financial (Fin.) and non-financial CFOs (Non-Fin.) over time. Risk expectations are the difference between the first and ninth decile return. The grey-shaded area denotes NBER recessions.

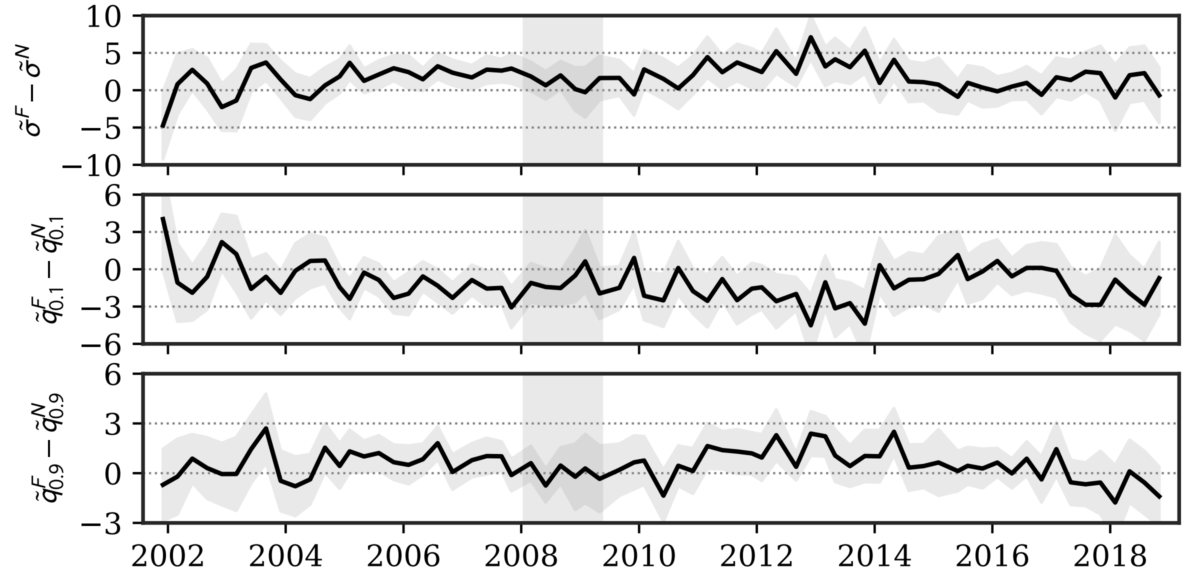

Fig. A3. Time Series of Risk Wedge

This figure shows differences in risk (upper panel), first decile return (middle panel), and ninth decile return (lower panel) expectations between financial (Fin.) and non-financial CFOs (Non-Fin.) over time. The grey-shaded area denotes the 90% confidence interval from a two-sample t-test, testing whether non-financial and financial CFOs have the same mean for each point in time.

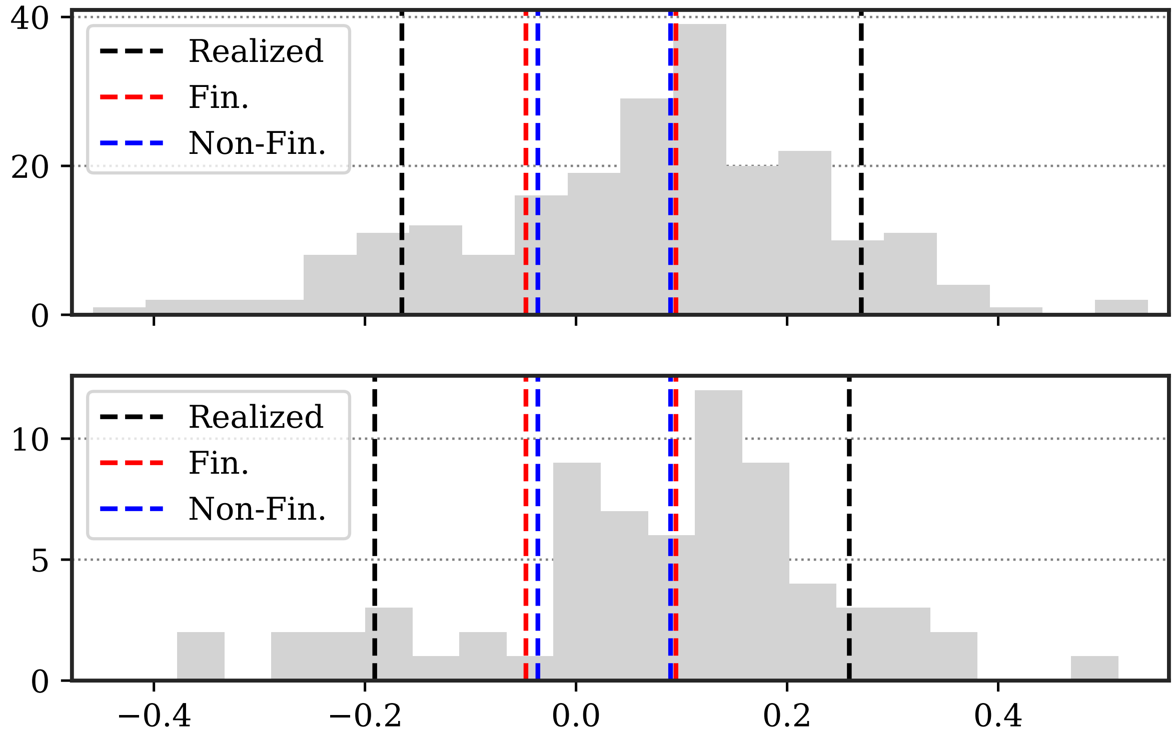

Fig. A4. Expected and Realized Return Distribution

This figure shows the expected and realized one-year return distribution. The grey barplots indicate the number of quarterly realized return observations from Q3 1963 to Q4 2018 (upper panel) and from Q4 2001 to Q4 2018 (lower panel), where the black dashed lines indicate the first decile (left) and ninth decile return (right). The red dashed lines show the average expected first (left) and ninth (right) decile return of financial CFOs, while the blue dashed lines present the average expected first (left) and ninth (right) decile return of non-financial CFOs.

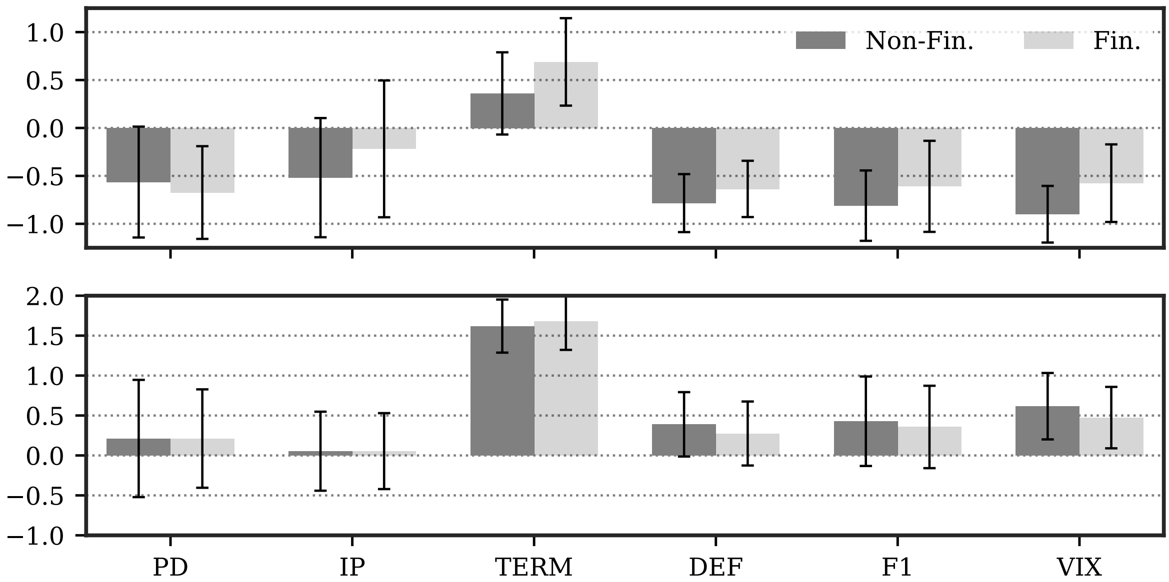

Fig. A5. Cyclicality of Upside and Downside Expectations

This figure reports coefficients from regressions of financial (Fin.) and non-financial CFO (Non-Fin.) downside (upper panel) and upside (lower panel) return expectations (in %) on standardized business cycle indicators. The bar denotes the coefficient, while the whiskers give the 95% confidence interval estimated using Newey and West (1987) standard errors (two lags). Upside and downside return expectations are the average expected ninth and first decile return. The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts.

Table A1: Regression of Return Wedge on Business Cycle Predictors

This table reports coefficients from regressions of the difference of excess return expectations (in %) of financial (Fin.) and non-financial CFOs (Non-Fin.) on standardized business cycle indicators. The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts. t-statistics are reported in parentheses and are estimated using Newey and West (1987) standard errors (two lags).

	$\tilde{\sigma}^F - \tilde{\sigma}^N$					
$x =$	PD	IP	TERM	DEF	F1	VIX
α	−0.000	−0.000	0.021	−0.000	−0.000	−0.000
	(−0.00)	(−0.00)	(0.27)	(−0.00)	(−0.00)	(−0.00)
x	0.012	0.103	0.096	−0.020	−0.002	−0.020
	(0.19)	(1.34)	(1.27)	(−0.35)	(−0.04)	(−0.27)
Obs.	69	69	67	69	69	69
R^2	0.00	0.02	0.02	0.00	0.00	0.00

Table A2: Regression of Downside Wedge on Business Cycle Predictors

This table reports coefficients from regressions of the difference between downside risk expectations (in %) of financial (Fin.) and non-financial CFOs (Non-Fin.) on standardized business cycle indicators. Downside risk expectations are the average expected first decile return. The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts. t-statistics are reported in parentheses and are estimated using Newey and West (1987) standard errors (two lags).

	$\tilde{\sigma}^F - \tilde{\sigma}^N$					
$x =$	PD	IP	TERM	DEF	F1	VIX
α	-1.133^{***}	-1.133^{***}	-1.139^{***}	-1.133^{***}	-1.133^{***}	-1.133^{***}
	(−5.78)	(−5.79)	(−6.07)	(−5.83)	(−5.73)	(−5.91)
x	−0.109	0.300^{**}	0.329^{***}	0.148	0.201	0.324^{**}
	(−0.50)	(2.31)	(2.56)	(1.51)	(1.51)	(2.13)
Obs.	69	69	67	69	69	69
R^2	0.01	0.04	0.05	0.01	0.02	0.05

Table A3: Regression of Upside Wedge on Business Cycle Predictors

This table reports coefficients from regressions of the difference between upside risk expectations (in %) of financial (Fin.) and non-financial CFOs (Non-Fin.) on standardized business cycle indicators. Upside risk expectations are the average expected ninth decile return. The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts. t-statistics are reported in parentheses and are estimated using Newey and West (1987) standard errors (two lags).

	$\tilde{\sigma}^F - \tilde{\sigma}^N$					
$x =$	PD	IP	TERM	DEF	F1	VIX
α	0.506***	0.506***	0.547***	0.506***	0.506***	0.506***
	(3.72)	(3.72)	(4.07)	(3.77)	(3.74)	(3.77)
x	−0.001	0.001	0.060	−0.115	−0.072	−0.143
	(−0.01)	(0.01)	(0.52)	(−1.55)	(−0.89)	(−1.55)
Obs.	69	69	67	69	69	69
R^2	0.00	0.00	0.00	0.02	0.01	0.02

Table A4: Regression of Sharpe Ratio Wedge on Business Cycle Predictors

This table reports coefficients from regressions of the difference of Sharpe Ratio expectations (in %) of financial (Fin.) and non-financial CFOs (Non-Fin.) on standardized business cycle indicators. The business cycle indicators include the negative price-dividend ratio (PD), the negative log growth in industrial production (IP), the difference between the 10-year and 3-month treasury yield (TERM), the difference between BAA and AAA bond yields (DEF), the Ludvigson and Ng (2009) macro factor (F1), and the CBOE Volatility Index (VIX). I use negative values for PD and IP so that positive coefficients for each predictor indicate counter-cyclicality of return forecasts. t-statistics are reported in parentheses and are estimated using Newey and West (1987) standard errors (two lags).

	$\tilde{\sigma}^F - \tilde{\sigma}^N$					
$x =$	PD	IP	TERM	DEF	F1	VIX
α	−0.083***	−0.083***	−0.083***	−0.083***	−0.083***	−0.083***
	(−4.10)	(−4.18)	(−4.17)	(−4.16)	(−4.10)	(−4.16)
x	−0.002	0.030***	0.012	0.014	0.016	0.029
	(−0.13)	(2.50)	(0.84)	(1.22)	(1.38)	(1.62)
Obs.	69	69	67	69	69	69
R^2	0.00	0.04	0.01	0.01	0.01	0.04

Appendix B. Asset Pricing Model

B.1. Optimization Problems

The economy has two types of agents: the household (HH) and the financial sector (FI). Both have standard mean-variance preferences with exponential utility and risk aversion parameters γ_H and γ_I. There is one riskless asset with payoff r and n risky assets with supply S. The payoffs of the risky assets are jointly normally distributed with mean μ and the positive definite variance-covariance matrix Σ. The agents decide at $t = 0$ to invest in the assets and receive the payoffs at $t = 1$.

The FI sets its demand vector D_I according to

$$\max_{D_I} \; D_I^{'}(\mu - \rho) - \frac{\gamma_I}{2} D_I^{'} \Sigma_I D_I, \tag{B1}$$

where μ is the payoff vector, ρ is the equilibrium price vector, γ_I is the constant risk aversion of the FI, and Σ_I is the subjective belief of the FI about the true covariance-variance matrix Σ. The optimal FI demand is then equal to

$$D_I^{*} = \frac{1}{\gamma_I} \Sigma_I^{-1} (\mu - \rho). \tag{B2}$$

The HH takes the demand of the FI as exogenous and faces quadratic costs for trading in risky assets. Thus, the household sets its demand D_H according to

$$\max_{D_H} (D_H + D_I)^{'} (\mu - \rho) - \frac{\gamma_H}{2} (D_H + D_I)^{'} \Sigma_H (D_H + D_I) - \frac{1}{2} D_H^{'} \Sigma_{diag,H} C D_H. \tag{B3}$$

Note that the first and second terms are equivalent to (B2) but additionally take the FI demand as exogenous. The third term captures the quadratic costs of household trading in the corresponding matrix C. Solving for the optimal demand gives

$$D_H^{*} = (\gamma_H \Sigma_H + \Sigma_{diag,H} C)^{-1} (\mu - \rho) - (\gamma_H \Sigma_H + \Sigma_{diag,H} C)^{-1} \gamma_H \Sigma_H D_I. \tag{B4}$$

FI and HH have biased expectations about the true covariance-variance matrix, i.e.,

$$\Sigma_I = (1 + \phi_I Z)\Sigma \tag{B5}$$

$$\Sigma_H = (1 + \phi_H Z)\Sigma \tag{B6}$$

where Z is an aggregate signal that affects the risk expectations of the agents but is unrelated to the asset variance. By assumption, it holds that $Z \in [0, 1]$, $\phi_I > -1$ and $\phi_H > -1$ to ensure that expected variances are always positive. Both FI and HH receive this signal and build their expectations based on their bias parameters ϕ_I and ϕ_H. Positive values lead to higher expectations than the actual variance and vice versa. If $\phi_H = \phi_I = 0$, agents have rational expectations, and the model collapses to Haddad and Muir (2021).

B.2. *Solving for the Expected Return*

In the following derivation, it will be useful to define

$$x = \gamma_H \Sigma + \Sigma_{diag} C \tag{B7}$$

$$x^{-1} = \gamma_H^{-1} \Sigma^{-1} - \gamma_H^{-1} \Sigma^{-1} \Sigma_{diag} C x^{-1} \tag{B8}$$

Market clearing implies

$$S = D_H^* + D_I^*. \tag{B9}$$

Substituting (B2), (B4), and (B7) in (B9) gives

$$\begin{aligned} S =& (1 + \phi_H Z)^{-1} (\gamma_H \Sigma + \Sigma_{diag} C)^{-1} (\mu - \rho) - (1 + \phi_H Z)^{-1} (\gamma_H \Sigma \\ & + \Sigma_{diag} C)^{-1} \gamma_H (1 + \phi_H Z) \Sigma D_I^* + D_I^* \\ =& ((1 + \phi_H Z)^{-1} x^{-1} - x^{-1} \gamma_H \frac{1}{\gamma_I} (1 + \phi_I Z)^{-1} + \frac{1}{\gamma_I} (1 + \phi_I Z)^{-1} \Sigma^{-1})(\mu - \rho) \end{aligned} \tag{B10}$$

Rearrange (B10) to get an expression of the expected return and define α

$$\mu-\rho=(x^{-1}((1+\phi_H Z)^{-1}-(1+\phi_I Z)^{-1}\frac{\gamma_H}{\gamma_I})+\frac{1}{\gamma_I}(1+\phi_I Z)^{-1}\Sigma^{-1})^{-1}S. \tag{B11}$$

$$=\alpha^{-1}S \tag{B12}$$

Solving for α using (B8) gives

$$\begin{aligned}\alpha=&x^{-1}((1+\phi_H Z)^{-1}-(1+\phi_I Z)^{-1}\frac{\gamma_H}{\gamma_I})+\frac{1}{\gamma_I}\Sigma^{-1}(1+\phi_I Z)^{-1}\\ =&\Sigma^{-1}\Big[\Sigma x^{-1}(1+\phi_H Z)^{-1}+\frac{1}{\gamma_I}\Sigma_{diag}Cx^{-1}(1+\phi_I Z)^{-1}\Big]\end{aligned} \tag{B13}$$

Substituting (B13) back into (B12) and inserting the expression for x in (B7) gives

$$\begin{aligned}(\mu-\rho)=&\alpha^{-1}S\\ =&\Sigma\Big[\Sigma(\gamma_H\Sigma+\Sigma_{diag}C)^{-1}(1+\phi_H Z)^{-1}\\ &+\frac{1}{\gamma_I}\Sigma_{diag}C(\gamma_H\Sigma+\Sigma_{diag}C)^{-1}(1+\phi_I Z)^{-1}\Big]^{-1}S.\end{aligned} \tag{B14}$$

This general solution nests the result of Haddad and Muir (2021) as a special case when $\phi_I=0$ and $\phi_H=0$. In this case, (B14) reduces to

$$\mu-\rho=\gamma_H\Sigma[\Sigma+\frac{1}{\gamma_I}\Sigma_{diag}C]^{-1}(\Sigma+\frac{1}{\gamma_H}\Sigma_{diag}C)S, \tag{B15}$$

which is exactly equation (10) in Haddad and Muir (2021).

To solve for the expected return of an asset, I follow Haddad and Muir (2021) and assume that $\Sigma_{diag}=\Sigma$. Then,

$$(\mu-\rho)=\Sigma\Sigma^{-1}\Big[[(1+\phi_H Z)^{-1}+\frac{1}{\gamma_I}C(1+\phi_I Z)^{-1}](\gamma_H\Sigma+\Sigma C)^{-1}\Big]^{-1}S \tag{B16}$$

$$=\Big[(1+\phi_H Z)^{-1}+\frac{1}{\gamma_I}C(1+\phi_I Z)^{-1}\Big]^{-1}(\gamma_H\Sigma+\Sigma C)S. \tag{B17}$$

Solving (B17) for an individual asset gives its expected return

$$\mu_i - \rho_i = \frac{\gamma_H + c_i}{(1+\phi_H z)^{-1} + (1+\phi_I z)^{-1}\frac{c_i}{\gamma_I}}\sigma_i^2 \tag{B18}$$

B.3. *Solving for Elasticities*

Now, I solve for three elasticities. First, the main prediction of my model is

$$\frac{\frac{1}{\mu_i-\rho_i}\frac{\partial \mu}{\partial z}}{\partial c} = \frac{(\phi_I - \phi_H)\gamma_I}{(c_i(1+\phi_H z_i) + \gamma_I(1+\phi_I z_i))^2}. \tag{B19}$$

The sign of this elasticity only depends on the difference $\phi_I - \phi_H$. Second and third, I derive the same elasticities as in Haddad and Muir (2021), i.e.,

$$\frac{1}{\mu_i - \rho_i}\frac{\partial(\mu_i - \rho_i)}{\partial log(\gamma_H)} = \frac{\gamma_H}{\gamma_H + c_i} \tag{B20}$$

and

$$\frac{1}{\mu_i - \rho_i}\frac{\partial(\mu_i - \rho_i)}{\partial log(\gamma_I)} = \frac{c_i}{\frac{1+\phi_I z}{1+\phi_H z}\gamma_I + c_i}. \tag{B21}$$

Compared to their model, (B20) is unchanged, indicating that the elasticity of expected asset returns with respect to HH risk aversion is unaffected by subjective and potentially biased risk beliefs. However, (B21) now additionally includes the scaling factor $\frac{1+\phi_I z}{1+\phi_H z}$, which is always positive by definition as variances cannot become negative ($\phi_I > -1$ and $\phi_H > -1$). While the effect size may differ, the sign does not change. Hence, all results from Haddad and Muir (2021) hold in my model, regardless of the respective bias parameters ϕ_I and ϕ_H.