*Internet Appendix:*

# Forward Return Expectations*

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## Contents



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# A Proofs

***Proof of Proposition 1.*** Given that $M_{t,t+n}R_{t,t+n} = 1$ by assumption, $\mathcal{C}_t^{(n)} = 0$ in (4). The stated results then follow immediately. $\square$

***Proof of Proposition 2.*** First consider $n = m = 1$, and write

$$\begin{aligned}\varepsilon_{t+1}^{(1)} = \mu_{t+1}^{(1)} - f_t^{(1)} = \mathscr{L}_{t+1}^{(1)} - \mathscr{L}_t^{(2)} + \mathscr{L}_t^{(1)} + \operatorname{cov}_t(MR_{t,t+2}, r_{t,t+2}) \\ - \operatorname{cov}_t(MR_{t,t+1}, r_{t,t+1}) - \operatorname{cov}_{t+1}(MR_{t+1,t+2}, r_{t+1,t+2}).\end{aligned} \tag{A1}$$

Consider the first covariance term. Given the joint log-normality of the SDF and returns (and the normality of $r_{t,t+n}$), Stein's lemma gives that

$$\begin{aligned}\operatorname{cov}_t(MR_{t,t+2}, r_{t,t+2}) &= \operatorname{cov}_t(MR_{t,t+1}MR_{t+1,t+2}, r_{t,t+2}) \\ &= \operatorname{cov}_t(mr_{t,t+1} + mr_{t+1,t+2}, r_{t,t+2})\, \mathbb{E}_t[MR_{t,t+2}] \\ &= \operatorname{cov}_t(mr_{t,t+1} + mr_{t+1,t+2}, r_{t,t+1} + r_{t+1,t+2}),\end{aligned}$$

where $mr_{t,t+n} = \ln(MR_{t,t+n})$, and where the last line uses that $\mathbb{E}_t[MR_{t,t+2}] = 1$. Having separated the two $MR$ terms, apply Stein's lemma again to obtain

$$\begin{aligned}\operatorname{cov}_t(MR_{t,t+2}, r_{t,t+2}) &= \operatorname{cov}_t(mr_{t,t+2}, r_{t,t+1}) + \operatorname{cov}_t(mr_{t,t+1}, r_{t+1,t+2}) + \operatorname{cov}_t(mr_{t+1,t+2}, r_{t,t+2}) \\ &= \operatorname{cov}_t(MR_{t,t+2}, r_{t,t+1}) + \operatorname{cov}_t(MR_{t,t+1}, r_{t+1,t+2}) \\ &\quad + \operatorname{cov}_t(MR_{t+1,t+2}, r_{t+1,t+2}).\end{aligned} \tag{A2}$$

For the first two terms in (A2), by the law of total covariance and using that $\mathbb{E}_{t+1}[MR_{t+1,t+2}] = 1$,

$$\begin{aligned}\operatorname{cov}_t(MR_{t,t+2}, r_{t,t+1}) &= \mathbb{E}_t\big[MR_{t,t+1}r_{t,t+1} \operatorname{cov}_{t+1}(MR_{t+1,t+2}, 1)\big] \\ &\quad + \operatorname{cov}_t(MR_{t,t+1}\, \mathbb{E}_{t+1}[MR_{t+1,t+2}], r_{t,t+1}) \\ &= \operatorname{cov}_t(MR_{t,t+1}, r_{t,t+1}),\end{aligned} \tag{A3}$$

$$\begin{aligned}\operatorname{cov}_t(MR_{t,t+1}, r_{t+1,t+2}) &= \mathbb{E}_t[MR_{t,t+1} \operatorname{cov}_{t+1}(1, r_{t+1,t+2})] + \operatorname{cov}_t(MR_{t,t+1}, \mathbb{E}_{t+1}[r_{t+1,t+2}]) \\ &= \operatorname{cov}_t(MR_{t,t+1}, \mathbb{E}_{t+1}[r_{t+1,t+2}]).\end{aligned} \tag{A4}$$

Turning now to the last term in (A1), the law of total covariance can similarly be applied to obtain that as of time $t$,

$$\mathbb{E}_t[\operatorname{cov}_{t+1}(MR_{t+1,t+2}, r_{t+1,t+2})] = \operatorname{cov}_t(MR_{t+1,t+2}, r_{t+1,t+2}). \tag{A5}$$

Taking expectations in (A1), substituting in results (A2)–(A5), and applying the definition of $\widehat{\varepsilon}_{t+1}^{(1)}$, we obtain:

$$\mathbb{E}_t\left[\varepsilon_{t+1}^{(1)}\right] = \mathbb{E}_t\left[\widehat{\varepsilon}_{t+1}^{(1)}\right] + \operatorname{cov}_t(MR_{t,t+1}, \mathbb{E}_{t+1}[r_{t+1,t+2}]). \tag{A6}$$

Rearranging to solve for $\mathbb{E}_t[\widehat{\varepsilon}_{t+1}^{(1)}]$ yields the stated result for the $n = m = 1$ case. While this case is convenient for straightforward derivations, note that all the above steps apply when using $t + n$ in place of $t + 1$ and using $t + n + m$ in place of $t + 2$, so the stated result holds for general $n, m$. $\square$

***Proof of Proposition 3.*** Starting again with (A1) and expanding the first covariance term,

$$\mathrm{cov}_t(MR_{t,t+2}, r_{t,t+2}) = \mathrm{cov}_t(MR_{t,t+1}MR_{t+1,t+2}, r_{t,t+1}) + \mathrm{cov}_t(MR_{t,t+1}MR_{t+1,t+2}, r_{t+1,t+2}). \quad \text{(A7)}$$

We consider each of the two terms on the right side of (A7) in turn, and in both cases apply the law of total covariance. For the first term, as in (A3),

$$\mathrm{cov}_t(MR_{t,t+1}MR_{t+1,t+2}, r_{t,t+1}) = \mathrm{cov}_t(MR_{t,t+1}, r_{t,t+1})\,. \quad \text{(A8)}$$

For the second term,

$$\begin{aligned}\mathrm{cov}_t(MR_{t,t+1}MR_{t+1,t+2}, r_{t,t+2}) = \mathbb{E}_t\big[&MR_{t,t+1}\,\mathrm{cov}_{t+1}(MR_{t+1,t+2}, r_{t+1,t+2})\big] \\ &+ \mathrm{cov}_t(MR_{t,t+1}, \mathbb{E}_{t+1}[r_{t+1,t+2}])\,. \end{aligned} \quad \text{(A9)}$$

Using (A8) and (A9) in (A1), applying the definition of $\widehat{\varepsilon}^{(1)}_{t+1}$, and taking expectations,

$$\begin{aligned}\mathbb{E}_t\left[\varepsilon^{(1)}_{t+1}\right] &= \mathbb{E}_t\left[\widehat{\varepsilon}^{(1)}_{t+1}\right] + \mathbb{E}_t[(MR_{t,t+1}-1)\,\mathrm{cov}_{t+1}(MR_{t+1,t+2}, r_{t+1,t+2})] \\ &\quad + \mathrm{cov}_t(MR_{t,t+1}, \mathbb{E}_{t+1}[r_{t+1,t+2}]) \\ &= \mathbb{E}_t\left[\widehat{\varepsilon}^{(1)}_{t+1}\right] + \mathrm{cov}_t(MR_{t,t+1}, \mathbb{E}_{t+1}[r_{t+1,t+2}] + \mathrm{cov}_{t+1}(MR_{t+1,t+2}, r_{t+1,t+2}))\,. \end{aligned} \quad \text{(A10)}$$

Note from (4) that $\mathscr{L}^{(1)}_{t+1} = \mathbb{E}_{t+1}[r_{t+1,t+2}] + \mathrm{cov}_{t+1}(MR_{t+1,t+2}, r_{t+1,t+2})$. Using this in (A10),

$$\mathbb{E}_t\left[\widehat{\varepsilon}^{(1)}_{t+1}\right] = \mathbb{E}_t\left[\varepsilon^{(1)}_{t+1}\right] - \mathrm{cov}_t\Big(MR_{t,t+1}, \mathscr{L}^{(1)}_{t+1}\Big)\,.$$

The above steps again apply when using $t+n$ in place of $t+1$ and using $t+n+m$ in place of $t+2$, completing the proof. □

***Proof of Lemma A1.*** To compute the risk-neutral expectation of $H[P_T] = R^{\alpha}(\ln R)^{\beta}$, we apply standard spanning theorems (Bakshi and Madan 2000, Carr and Madan 2001). We have

$$\begin{aligned}\frac{1}{R_f}\,\mathbb{E}^*_t\left[R^{\alpha}(\ln R)^{\beta}\right] &= \left(H\left[\bar{P}\right] - \bar{P}H_P\left[\bar{P}\right]\right)\frac{1}{R_f} + H_P\left[\bar{P}\right]P_t \\ &\quad + \int_0^{\bar{P}} H_{PP}[K]\,\mathrm{put}^{(n)}_t(K)dK + \int_{\bar{P}}^{\infty} H_{PP}[K]\,\mathrm{call}^{(n)}_t(K)dK.\end{aligned}$$

The result follows by setting $\bar{P} = F^{(n)}_t$ and simplifying. □

***Proof of Proposition A1.*** (A13) is immediate from Martin (2017) Result 8. (A14) and (A15) follow from Lemma A1 by setting the appropriate $\alpha$ and $\beta$ and simplifying. □

# B Measurement Details

## B.1 Data

**United States Data.** For the 1996 to 2021 period, we obtain end-of-day option prices, index prices, projected dividend yields, and risk-free rates from OptionMetrics. To maximize the sample size, we use options with both AM and PM settlement. We use the bid/ask midpoint as the option price in

the main analysis. We linearly interpolate the risk-free rate curve to match option maturities. If either the dividend yield or risk-free rate is missing, we use the last non-missing observation.

For the 1990 to 1995 period, we obtain intraday option quotes from CBOE Market Data Express, as in Kelly, Pástor, and Veronesi (2016) and Culp, Nozawa, and Veronesi (2018). We obtain end-of-day index prices/returns from CRSP and estimate dividend yields from lagged one-year cum/ex-dividend index returns. We obtain Treasury bill rates and constant maturity Treasury yields from FRED to construct risk-free rates, as in Culp, Nozawa, and Veronesi.

Unlike OptionMetrics, CBOE provides intraday quotes. To construct end-of-day prices, we first apply filters to the intraday data and then use the last available quote. We drop quotes with the missing codes of 998 or 999. We drop quotes with negative bid-ask spreads. We correct erroneously recorded quotes – quotes with strike price less than 100 – by multiplying the strike/option price by 10. We drop end-of-day quotes that increase and then decrease fourfold (or vice versa), following similar filters in Andersen, Bondarenko, and Gonzalez-Perez (2015) and Duarte, Jones, and Wang (2022). We interpret these large reversals as probable data errors. To validate these filters, we compare data from CBOE and OptionMetrics in 1996. We match approximately 99.3% of option prices in OptionMetrics, suggesting these filters are not unreasonable.

We apply standard filters to the end-of-day data (Constantinides, Jackwerth, and Savov 2013). (1) We drop options with special settlement. (2) To eliminate duplicate quotes, we select the quote with highest open interest. (3) We drop options with fewer than seven days-to-maturity. (4) We drop options with price less than 0.01. (5) We drop options with zero bid prices or negative bid-ask spreads. (6) We drop options that violate static no-arbitrage bounds:

$$\text{put}_t^{(n)}(K) \leq Ke^{-r\tau} \qquad \text{call}_t^{(n)}(K) \leq P_t.$$

(7) We drop options for which the Black-Scholes implied volatility computation does not converge and options with implied volatility less than 5% or greater than 100%.

**International Data.** We again obtain end-of-day option prices, index prices, projected dividend yields, and risk-free rates from OptionMetrics. Unlike the United States, most option prices are either end-of-day settlement prices or last traded prices. Only a small fraction are from either bid/ask prices. The index price is time synchronized to the option price. If the index price is missing, we obtain the end-of-day price from Compustat Global. Risk-free rates are from currency-matched LIBOR curves. Dividend yields are from put-call parity and so are maturity-specific. As before with risk-free rates, we linearly interpolate the dividend yield curve to match option maturities. We apply the same filters to the end-of-day data as with the United States, except for filters that require bid/ask prices.

Table A1 describes the international sample. The European sample begins in January 2002 and ends in September 2021. The Asian sample begins in January 2004 and ends in April 2021. Our international sample closely follows Kelly, Pástor, and Veronesi (2016) and Dew-Becker and Giglio (2021), but we also use pan-European Stoxx indexes. These indexes represent a substantive addition to the sample. At long maturities, the Euro Stoxx 50 is arguably the most liquid options market in the world, as is the case with the dividend futures market (Binsbergen and Koijen 2017, Binsbergen et al. 2013).

**Main Sample.** As the international data is not equally robust across exchanges, we select the most reliable exchanges for the main analysis. We select the main sample by elimination. We drop Netherlands and Japan because they do not have sufficiently dense options, as seen in Panel A of Figure A1. We drop Finland, the Stoxx Europe 50, and the Stoxx Europe 600 because they do not

have reliable open interest data, as seen in Panel B of Figure A1. We drop Belgium, Korea, and Taiwan because they do not consistently have long-maturity options, as seen in Panel D of Figure A2. We drop China and Sweden because they do not have sufficiently deep out-of-the-money options, as seen in Figure A2. This leaves the 10 exchanges in the last column of Table A1 for the main sample. As a robustness check, we examine the full sample of 20 exchanges in Table A8 and Table A10.

### B.2 Baseline Measures

**Methodology.** On each date and separately for puts/calls,

1. We convert option prices to implied volatilities via Black-Scholes. Here we follow an extensive literature on option-implied risk-neutral densities that finds interpolation more conducive in the space of implied volatilities, not option prices (Figlewski 2010, Malz 2014).

2. We fit a Delaunay triangulation to implied volatilities. The grid consists of strike prices between $\underline{K} = 0.10 \times P_t$ and $\overline{K} = 2.00 \times P_t$ with $\Delta K = 0.001 \times P_t$ and maturities $\tau = 30$, 60, 91, 122, 152, 182, 273, 365 days. The triangulation extrapolates as necessary with the nearest implied volatility in moneyness and time-to-maturity space.

3. We convert the triangulation of implied volatilities back to option prices via Black-Scholes. We then use the implied triangulation of option prices to evaluate the LVIX integral in (7) via Gaussian quadrature.

4. With the LVIX in hand, we can immediately compute spot rates, forward rates, and forecast errors under log utility via Proposition 1, as shown in Figure A3. Figure A4 plots contemporaneous 6-month spot rates and $6 \times 6$-month forward rates in the full sample, analogous to Figure 2 in the United States.

5. We occasionally find negative forward rates. Gao and Martin (2021) argue that negative forward rates are unlikely theoretically and likely represent data errors. We follow Gao and Martin and drop such observations, but our results are not quantitatively sensitive to this choice.

**Discussion.** Three empirical challenges in the computation of option-implied moments – discretization, truncation, and interpolation bias – motivate our baseline methodology (Carr and Wu 2009, Jiang and Tian 2007). We discuss each in turn. First, discretization bias arises because (7) requires numerical integration. To minimize this bias, we integrate on a fine grid of interpolated option prices in step 3. Second, truncation bias arises because (7) requires integration over an infinite range of strike prices in theory. In practice, we truncate the integral. To minimize this bias, we extrapolate and integrate over strike prices well beyond the range of observable option prices in step 2. Finally, interpolation bias arises because (7) usually requires options with unavailable maturities. To address this bias, we interpolate the option surface at target maturities in step 2.

**Measurement Error.** To better understand the role of measurement error, Figure A5 examines spot/forward rates in simulations. We first compute option prices from a parametric model. Since we know the true data generating process, we then quantify how varying integration bounds affects the integral relative to the true value. The thought experiment follows a similar exercise in Jiang and Tian (2007) for the VIX.

We first truncate the integral (7) without extrapolation, as in Table A3. In Panel A, we consider a Black-Scholes model. We find a large truncation bias in bad times. In bad times, volatility is

high, deep out-of-the-money options are expensive, and so the bias is large. In contrast, in good times, volatility is low, deep out-of-the-money options are cheap, and so the bias is small. The bias is especially large for 12-month spot rates and forward rates because longer-maturity option prices have more time value. In Panel B, we consider a stochastic volatility model with jumps (SVJ). We again find an uncomfortably large truncation bias. Relative to Black-Scholes, the bias is larger when volatility is low, but smaller when volatility is high because volatility mean-reverts in SVJ.

We next truncate the integral after extrapolating beyond the range of observable strikes, as in the baseline analysis. We continue with a SVJ model in Panel C. Relative to Panel B, we find that extrapolation reduces truncation bias across the board.

We emphasize, however, that this exercise only motivates extrapolation in our baseline integration scheme and our use of shorter-maturity forward rate as instruments/predictors, as in Table 3 and Table 5. We make no claim that measurement error is unconditionally small. By construction, these simulations address only truncation bias. There is no scope for either discretization or interpolation bias, as we simulate option prices on a counterfactually dense grid. We think these biases may be non-trivial at times and especially so when options are less dense.

## B.3 Alternative Measures

Table A3 reports robustness checks where we use alternative choices to measure spot rates, forward rates, and forecast errors. As we discuss below, the main results are largely robust to these choices.

**Integration Bounds.** Panel A repeats the analysis with alternative integration bounds. The first four rows consider static bounds without extrapolation. As an example, the first row evaluates the integral in (7) between strike prices $\underline{K} = 0.65 \times P_t$ and $\overline{K} = 1.35 \times P_t$ at each maturity. The fifth row uses observable option prices between strike prices $\underline{K} = 0.10 \times P_t$ and $\overline{K} = 2.00 \times P_t$, again without extrapolation. The bounds in the first five rows naturally vary both by time and maturity with the availability of option prices. The sixth row considers static bounds with extrapolation, following a similar robustness check in Gormsen and Jensen (2022):

$$\left[\underline{K}^{(n)}, \overline{K}^{(n)}\right] = \begin{cases} [0.75, 1, 25] \times P_t & n \in \{1,2\} \\ [0.55, 1.45] \times P_t & n \in \{3,4,5\} \\ [0.35, 1.65] \times P_t & n \in \{6,9\} \\ [0.20, 1.80] \times P_t & n \in \{12\} \,. \end{cases}$$

These bounds vary by maturity, but not by time. The seventh row considers dynamic bounds with extrapolation, again following a similar robustness check in Gormsen and Jensen:

$$\underline{K}^{(n)} = \max\left\{0.10, 1.00 - 5\sigma_t^{(n)}\sqrt{\tau}\right\} \times P_t \qquad \overline{K}^{(n)} = \min\left\{2.00, 1.00 + 5\sigma_t^{(n)}\sqrt{\tau}\right\} \times P_t,$$

where $\sigma_t^{(n)}$, the price of the volatility contract in Bakshi, Kapadia, and Madan (2003), proxies for the risk-neutral volatility of the market return:

$$\begin{aligned} \left(\sigma_t^{(n)}\sqrt{\tau}\right)^2 &= \frac{1}{R^f_{t,t+n}}\mathbb{E}_t^*\left[(\ln R_{t,t+n})^2\right] \\ &= \int_0^{P_t} \frac{2\left(1+\ln\left[\frac{P_t}{K}\right]\right)}{K^2}\,\text{put}_t^{(n)}(K)dK + \int_{P_t}^{\infty} \frac{2\left(1+\ln\left[\frac{P_t}{K}\right]\right)}{K^2}\,\text{call}_t^{(n)}(K)dK. \end{aligned} \tag{A11}$$

These bounds vary by both time and maturity with volatility. The eighth row considers the baseline integration bounds, as discussed in the main text and Appendix B.2.

In sum, this exercise illustrates the significant effect truncation/extrapolation have on the regression estimates. With shallow bounds, forecast errors are relatively large on average but less predictable. With deep bounds, forecast errors are relatively small on average but more predictable.

**Liquidity Filters.** Panel B repeats the analysis with alternative liquidity filters. The first row considers an outlier filter, following similar filters in Constantinides, Jackwerth, and Savov (2013) and Beason and Schreindorfer (2022). On each date and separately for puts/calls, we first fit a quadratic function to implied volatilities in terms of moneyness $K/P$ and time-to-maturity. To minimize the effect of deep out-of-the-money, short/long-maturity options, we only use options with maturity $14 \leq \tau \leq 365$ days and moneyness $0.65 \leq K/P \leq 1.35$. We then drop influential observations via Cook's Distance. The second row considers an open interest filter. We drop options with zero open interest. We do not have open interest data before 1996. The third row combines the outlier and open interest filters. In all, this exercise is consistent with the baseline results, suggesting that option illiquidity does not explain our findings.

**Volatility Surface.** The first row in Panel C repeats the analysis with the interpolated volatility surface from OptionMetrics. OptionMetrics provides interpolated Black-Scholes implied volatilities on a constant moneyness/maturity grid. The literature often uses this surface for options with American exercise because OptionMetrics reports an equivalent, European exercise, implied volatility (Kelly, Lustig, and Van Nieuwerburgh 2016, Martin and Wagner 2019). We instead simply use it as a robustness check on our own Delaunay triangulation of the volatility surface. In short, this exercise is consistent with the baseline results, although the average forecast error is somewhat smaller.

**SVI Surface.** The second row in Panel C repeats the analysis with the stochastic volatility inspired (SVI) surface from Jim Gatheral at Merrill Lynch (Gatheral 2011, Gatheral and Jacquier 2011, 2014). Our implementation of the SVI surface closely follows Berger, Dew-Becker, and Giglio (2020) and Beason and Schreindorfer (2022). We parameterize squared Black-Scholes implied volatilities with the function

$$\sigma_{BS}^2(t, \kappa, \tau) = a + b\left(\rho(\kappa - m) + \sqrt{(\kappa - m)^2 + \sigma^2}\right), \tag{A12}$$

where $\kappa$ is standardized forward moneyness

$$\kappa = \frac{\ln K - \ln F_t^{(n)}}{\sigma_t^{(n)}\sqrt{\tau}},$$

$\sigma_t^{(n)}$ proxies for the risk-neutral volatility of the market return as in (A11), and each parameter is a linear function of time-to-maturity (e.g., $a = a_0 + a_1\tau$). On each date, we estimate parameters $\theta = (a_0, a_1, b_0, b_1, \rho_0, \rho_1, m_0, m_1, \sigma_0, \sigma_1)$ that minimize the implied volatility RMSE between the surface (A12) and the data, subject to standard no-arbitrage constraints: option prices are nonnegative and monotonic/convex in $K$ (Aït-Sahalia and Duarte 2003). We check these constraints on a grid with moneyness between $-20 \leq \kappa \leq 0.50$ for puts, between $-0.50 \leq \kappa \leq 10$ for calls, and maturities $\tau = 30, 60, 91, 122, 152, 182, 273, 365$ days. We estimate the surface with outlier-filtered, as discussed in Appendix B.3, out-of-the-money puts/calls: puts with $\kappa \leq 0$ and calls with $\kappa \geq 0$. We estimate the surface separately for puts/calls and separately for short/long-maturity options: $14 \leq \tau \leq 122$ days and $122 < \tau \leq 365$ days, respectively.

**Bid/Ask Prices.** Panel D repeats the analysis with bid/ask prices, following similar robustness checks in Martin (2017) and Gao and Martin (2021). We only have bid/ask prices in the United States. The first row reports the baseline results with the bid-ask midpoint. The second row repeats the analysis with bid prices, the third ask prices. In sum, this exercise is consistent with the baseline results, although the Coibion-Gorodnichenko regression slope is somewhat smaller with ask prices.

# C Additional Empirical Results and Robustness Checks

## C.1 Coibion-Gorodnichenko Regressions

**Methodology.** Here, we study the predictability of forecast errors using forward-rate *changes* (rather than levels, as in the main text), using the method in Coibion and Gorodnichenko (2015). This allows us to address more specifically whether forward rates exhibit excess sensitivity to news. These regressions take the following form:

$$\tilde{\varepsilon}^{m}_{i,t+n} = \beta_0 + \beta_1 \left( \tilde{f}^{(n,m)}_{i,t} - \tilde{f}^{(n+h,m)}_{i,t-h} \right) + e_{i,t+m},$$

for both option-based risk premia and expected returns. We consider multiple horizons for the forecast revision and forecast error.

**Results.** Table A4 presents results. We find, consistent with the main analysis, meaningful forecast-error predictability with significantly negative coefficients at multiple (though not all) horizons. The long-horizon risk-premium revisions generate more consistent significance in predictability, consistent with the fact that forward rates are persistent (so short-horizon revisions contain quite a bit of noise unrelated to the predictable component of forecast errors).

**Measurement Error.** In Coibion-Gorodnichenko regressions, we use forecast revisions to predict forecast errors. Since forecast revisions/errors involve the same forward rate, measurement error may produce spurious evidence of predictability. To better understand the role of measurement error, we again turn to simulations. We quantify how much correlated measurement error would be necessary to produce the Coibion-Gorodnichenko regression slopes in the data.

We assume we observe forecast revisions and forecast errors with noise:

$$\widetilde{x} = x\sigma_x + v\sigma_v \text{ and } \widetilde{y} = y\sigma_y - v\sigma_v,$$

respectively, with $\sigma_{xy} = \sigma_{xv} = \sigma_{yv} = 0$ and $x, y, v \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$. We vary $\sigma_v^2$ exogenously. In each simulation draw, we set the variance of the truth ($\sigma_x^2$ and $\sigma_y^2$) such that the observed variance ($\sigma_{\widetilde{x}}^2$ and $\sigma_{\widetilde{y}}^2$) equals that in the data. As $\sigma_v^2$ varies, these weights ensure all variation in slopes comes from variation in noise and none from variation in observed variances. Any evidence of predictability – any non-zero slope – is spurious because $\sigma_{xy} = 0$.

Figure A6 reports the results from these simulations. To produce the Coibion-Gorodnichenko regression slopes in the data, we require $\sigma_v$ be about 40 basis points or more than one-quarter the volatility of forecast errors in the data. This, at least to us, seems implausibly large. We conclude that correlated measurement error cannot fully explain forecast-error predictability in Coibion-Gorodnichenko regressions, although we cannot fully rule out some bias due to measurement error.

## C.2 Power Utility Regressions

**Methodology.** This section derives the power utility analogue to the LVIX. To do so, we apply results from Martin (2017) and Gao and Martin (2021). We omit time subscripts throughout to minimize clutter.

**LEMMA A1 (Spanning $R^{\alpha}(\ln R)^{\beta}$).** *For any $\alpha$ and $\beta$,*

$$\frac{1}{R_f}\mathbb{E}_t^*\left[R^{\alpha}(\ln R)^{\beta}\right] = R_f^{\alpha}(\ln R_f)^{\beta} + \int_0^{F_t^{(n)}} \omega(\alpha,\beta)\,\mathrm{put}_t^{(n)}(K)dK + \int_{F_t^{(n)}}^{\infty} \omega(\alpha,\beta)\,\mathrm{call}_t^{(n)}(K)dK,$$

*where*

$$\omega(\alpha,\beta) = -\frac{\alpha(1-\alpha)m^{\beta} + \beta(1-2\alpha)m^{\beta-1} + \beta(1-\beta)m^{\beta-2}}{P_t^2}\left(\frac{K}{P_t}\right)^{\alpha-2}$$

*and $m = \ln K - \ln P_t$.*

As is well-known, under certain regularity conditions, we can compute the price of any function of the index price via a replicating portfolio of bonds, stocks, and options. We simply apply this result to the function $R^{\alpha}(\ln R)^{\beta}$, which is useful for expectations under power utility below.

**PROPOSITION A1 (Expected Equity Premium with Power Utility).** *From the standpoint of an unconstrained power utility investor fully invested in the market,*

$$\mathbb{E}_t[\ln R] - \ln R_f = \frac{\mathbb{E}_t^*[R^{\gamma}\ln R]}{\mathbb{E}_t^*[R^{\gamma}]} - \ln R_f, \tag{A13}$$

*where*

$$\frac{1}{R_f}\mathbb{E}_t^*[R^{\gamma}\ln R] = R_f^{\gamma}\ln R_f + \int_0^{F_t^{(n)}} \omega(\gamma,1)\,\mathrm{put}_t^{(n)}(K)dK + \int_{F_t^{(n)}}^{\infty} \omega(\gamma,1)\,\mathrm{call}_t^{(n)}(K)dK \tag{A14}$$

*and*

$$\frac{1}{R_f}\mathbb{E}_t^*[R^{\gamma}] = R_f^{\gamma} + \int_0^{F_t^{(n)}} \omega(\gamma,0)\,\mathrm{put}_t^{(n)}(K)dK + \int_{F_t^{(n)}}^{\infty} \omega(\gamma,0)\,\mathrm{call}_t^{(n)}(K)dK \tag{A15}$$

*and $\gamma$ is the investor's risk aversion.*

The LVIX uses a special case of (A13) with $\gamma = 1$, and so the mechanics under power utility are similar, if only messier, to that under log utility. However, there is one caveat: as risk aversion $\gamma$ increases, the weights $\omega(\gamma,0)$ and $\omega(\gamma,1)$ on deep out-of-the-money call options become untenably large. Unfortunately, these options are largely unobservable. As such, we can only realistically measure expectations for a $\gamma \leq 3$ investor in practice.

Armed with the expected equity premium from the standpoint of a power utility investor, we can compute spot rates, forward rates, and forecast errors in the usual way.

**Results.** Table A5 presents results for option-based risk-premium and expected-return forecast errors when re-estimated under the assumption of an unconstrained investor with power utility, rather than log utility, for different values of constant relative risk aversion. Figure A7 provides a visual representation of these results. See Section 4.1.5 in the text for a discussion of the results.

## C.3 Long-Horizon Forecast Errors

For the forecast-error quantification in Section 5.1, we re-estimate spot rates, forward rates, and forecast errors at longer horizons (up to $m + n = 8$ years) for the Euro Stoxx 50. The sample runs from September 2005 through September 2014 (beyond which we cannot yet observe realized forecast errors). The combinations of $m$ and $n$ (in months) can be seen in Table A6. For each such combination, we predict forecast errors as in (9) using a regression of realized forecast errors on shorter-horizon forward rates; we use the $n - 12 \times 12$ forward rate (with horizons again now in months) for $n \geq 24$, and for $n = 12$ we use the $6 \times 6$ rate. After obtaining these predicted forecast errors, we calculate a decay parameter for each date's forecast errors, $\phi_t^{(n,m)}$, as the ratio of estimated $\mathbb{E}_t[\varepsilon_{t+n}^{(m)}]$ to $\mathbb{E}_t[\varepsilon_{t+12}^{(12)}]$ for each available $m, n > 12$. This decay specification builds on the one used by De la O and Myers (2021, eq. (13)) for expected returns, but we estimate it directly for each date $t$ (whereas they use a full-sample regression for one horizon). The entries of Table A6 report the median decay parameter over all $t$ for each combination of $m$ and $n$. In all cases the estimates are close to or above 1. Assuming that predictable forecast errors are permanent at all horizons might be thought of as providing an estimate of their maximal possible effect. That said, when we estimate the decay parameter in the U.S. (at shorter horizons, unreported), we in fact generally obtain estimates greater than 1, suggesting that setting $\phi^{(n,m)} = 1$ may, if anything, be slightly conservative in the U.S. sample.

## C.4 Monetary Policy Shocks

**Methodology.** While a full accounting of the drivers of forecast errors is beyond the scope of the paper, here we consider one leading candidate: unexpected monetary policy shocks. We separately consider forecast errors for the risk-free rate and for the option-based risk premium (which together add up to the expected-return forecast errors). For the risk-free rate, the forecast error is the difference between the forecast error on the option-based expected return and the option-based risk premium. For each of the two sets of realized forecast errors, we then run time-series regressions — separately for the U.S. and the Eurozone — of forecast errors on contemporaneous monetary policy shocks:

$$\tilde{\varepsilon}_{t+6}^{(6)} = \beta_0 + \beta_1 \left( \sum_{h=1}^{6} \mathrm{MPS}_{t+h} \right) + e_{t+6},$$

where $\mathrm{MPS}_{t+h}$ is a monetary policy shock measure for month $t + h$. The summed measure is contemporaneous to the 6-month forecast error, and the spot-rate horizon is 6 months. For $\mathrm{MPS}_{t+h}$ in the U.S., we consider fed funds rate changes and surprises from Bernanke and Kuttner (2005, BK), obtained from Ken Kuttner's website; target shocks and path shocks from Gürkaynak, Sack, and Swanson (2005, GSS), obtained via Acosta (2023) from Miguel Acosta's website; and fed funds rate shocks and policy news shocks from Nakamura and Steinsson (2018, NS), also obtained from Miguel Acosta's website. For the Eurozone, we consider target shocks, forward guidance shocks, and risk premium shocks from Leombroni et al. (2021, LVVW), obtained from Andrea Vedolin's website. In all cases, we report the $R^2$ from the above regression, as well as the correlation between the two variables.

**Results.** Table A7 presents results. We find strong, positive correlations in most cases between the risk-free rate forecast error and the monetary policy shocks, particularly the shocks related to *future* policy expectations like the GSS path shock or the NS policy news shock (as should be expected given that these are forecast errors for expected future short-term rates). We find more limited explanatory power ($R^2$) for equity risk-premium forecast errors, indicating that these are not largely

driven by monetary policy shocks. That said, the shocks still explain some of the forecast errors, and there are meaningful negative correlations: monetary policy tightening that was unexpected ex ante tends to correlate with future risk-premium spot rates being lower than predicted according to the forward rates, consistent with improving economic conditions. This is also potentially consistent with the monetary policy shocks partially driving the decreases in spot rates, along the lines of the information effect discussed by Nakamura and Steinsson (2018) (see also Golez and Matthies 2023).

### C.5 Additional Robustness Checks

**Alternative Samples.** Table A8 considers how our results extend to the full sample with all 20 available exchanges, as opposed to the 10 developed-market exchanges used in our main panel. The table presents results from a concise set of key regressions from Tables 2–5 in the main text. The main results hold here. The Mincer-Zarnowitz regression coefficients are similar to (in fact slightly below) the results in the main sample; the average forecast error is nearly identical to that in the main sample; and the error-predictability and Coibion-Gorodnichenko results are slightly stronger in the extended sample than in the main sample.

**Alternative Horizons.** Table A9 examines alternative horizons for Mincer-Zarnowitz, average error, and error-predictability regressions. The baseline analysis in Section 4 considers the 6-month spot rate in 6 months ($n = m = 6$ in Panel E). This exercise illustrates the effect of the horizon on the regression estimates. Holding $n + m$ fixed, forecast errors are relatively small on average and less predictable with small $n$; forecast errors are relatively large on average and more predictable with large $n$.

**Additional Robustness Checks.** Table A10 examines additional robustness checks. Panel A reports the baseline results. Panel B winsorizes spot rates, forward rates, forecast errors, and forecast revisions at the 2.5% level by exchange. Panel C is the trimming analogue to Panel B. Panel D repeats the analysis in balanced panels. Panel E repeats the analysis in subsamples. This exercise is generally consistent with the baseline results, although the Coibion-Gorodnichenko regression slopes are sensitive to winsorization/trimming and the forecast errors are somewhat less predictable in the later subsample.

## D Additional Model Discussion: A Trilemma for Expectation Errors

This appendix continues the discussion in Section 6.3 on how different moments of the data are tied together by the cyclicality of forecast errors. We begin with the Campbell-Shiller price-dividend decomposition in (11). Assume that the expectations $\mathbb{E}_t[\cdot]$ in that decomposition refer to agents' subjective beliefs, and $p_t - d_t$ is the observed log price-dividend ratio. Now consider an alternative economy in which all agents have rational expectations. For arbitrary equilibrium variable $x_t$ in the observed data, denote the corresponding variable in the alternative RE economy by $x_t^{RE}$. Define the wedge between these two variables to be $\widetilde{x}_t = x_t - x_t^{RE}$. For example, $\widetilde{p_t - d_t}$ is the wedge between the observed price-dividend ratio and the one that would be observed in the alternative economy with RE. Up to a constant, it satisfies

$$\widetilde{p_t - d_t} = \widetilde{CF}_t - \widetilde{\mathcal{F}}_t - \widetilde{RF}_t. \tag{A16}$$

Assume for simplicity that $\widetilde{RF}_t = 0$. The following variance decomposition for the price-dividend wedge therefore holds:

$$\operatorname{var}\left(\widetilde{p_t - d_t}\right) = \operatorname{var}\left(\widetilde{CF}_t\right) + \operatorname{var}\left(\widetilde{\mathcal{F}}_t\right) - 2\operatorname{cov}\left(\widetilde{CF}_t, \widetilde{\mathcal{F}}_t\right). \tag{A17}$$

Alternatively, one can also use the following decomposition given (A16):

$$\operatorname{var}\left(\widetilde{p_t - d_t}\right) = \operatorname{cov}\left(\widetilde{p_t - d_t}, \widetilde{CF}_t\right) - \operatorname{cov}\left(\widetilde{p_t - d_t}, \widetilde{\mathcal{F}}_t\right). \tag{A18}$$

The wedges $\widetilde{CF}_t$ and $\widetilde{\mathcal{F}}_t$ can be understood as expectation errors along the lines considered in Section 6: if subjective expectations are too high relative to RE, then the wedge will be positive (and forecast errors, defined as realized − forecast, are likely to be negative). According to either of the decompositions in (A17)–(A18), therefore, one must choose from at most two of the following three features of any model of expectation errors:

1. Volatile expectation errors for returns (and/or fundamentals)
2. Volatile price-dividend ratio relative to a rational benchmark
3. Countercyclical return expectation errors (positive return expectation errors in bad times)

For example, if excessively positive cash-flow and return forecast revisions occur in good times (after positive news), then $\operatorname{cov}\left(\widetilde{CF}_t, \widetilde{\mathcal{F}}_t\right) > 0$ in (A17). Alternatively, in the version expressed in (A18), positive comovement between price-dividend and forward-rate wedges similarly detracts from a model's ability to generate volatile $\widetilde{p_t - d_t}$. This form of overreaction to *realized outcomes* (cash flows and/or returns) may be intuitively appealing, but it limits a model's ability to speak to variation in the price-dividend ratio through expectation errors alone.[1]

Our empirical results, and our model of expectation errors, instead suggest overreaction of forward rates to *spot rates*, rather than realized returns. Unlike realized returns, we find that spot and forward rates *increase* in bad times. The negative covariance between fundamental news and return expectation errors in principle allows for a volatile price-dividend ratio.

[1] For example, Nagel and Xu (2022) obtain a price-dividend ratio volatility about 50% lower than that observed in the data (see their Table 5). Similarly, De la O and Myers (2021) report that in the model of Barberis et al. (2015), "movements in dividend change expectations are almost completely negated by movements in price change expectations. This leads to low variation in the price-dividend difference" (p. 1370); Campbell (2017) provides a related discussion of the Barberis et al. (2015) results.

# Appendix Tables and Figures

**Table A1**
**Option Sample**

This table reports the region, the abbreviation, the underlying index, the sample period, and the sample length in months for each exchange. The last column indicates whether the exchange is in the main sample. See Appendix B.1 for more details.

| Region | Abbrv | Index | Start | End | Length | Main |
|---|---|---|---|---|---|---|
| **North America** | | | | | | |
| United States | USA | S&P 500 | 199001 | 202112 | 384 | Y |
| **Europe** | | | | | | |
| Belgium | BEL | BEL 20 | 200201 | 202109 | 228 | |
| Switzerland | CHE | SMI | 200201 | 202109 | 237 | Y |
| Germany | DEU | DAX | 200201 | 202109 | 237 | Y |
| Spain | ESP | IBEX 35 | 200610 | 202109 | 180 | Y |
| Finland | FIN | OMXH25 | 200201 | 202109 | 237 | |
| France | FRA | CAC 40 | 200304 | 202109 | 222 | Y |
| United Kingdom | GBR | FTSE 100 | 200201 | 202109 | 237 | Y |
| Italy | ITA | FTSE MIB | 200610 | 202109 | 180 | Y |
| Netherlands | NLD | AEX | 200201 | 202109 | 219 | |
| Sweden | SWE | OMXS30 | 200705 | 202109 | 173 | |
| **Pan-Europe** | | | | | | |
| Euro Stoxx 50 | SX5E | SX5E | 200201 | 202109 | 237 | Y |
| Stoxx Europe 50 | SX5P | SX5P | 200201 | 202109 | 237 | |
| Stoxx Europe 600 | SXXP | SXXP | 200509 | 202109 | 193 | |
| **Asia-Pacific** | | | | | | |
| Australia | AUS | ASX 200 | 200401 | 202104 | 208 | Y |
| China | CHN | HSCEI | 200601 | 202104 | 184 | |
| Hong Kong | HKG | Hang Seng | 200601 | 202104 | 184 | Y |
| Japan | JPN | Nikkei 225 | 200405 | 202104 | 204 | |
| Korea | KOR | KOSPI 200 | 200407 | 202104 | 202 | |
| Taiwan | TWN | TAIEX | 200510 | 202104 | 187 | |

## Table A2
## Summary Statistics

This table reports summary statistics for option-based risk premia (left panel) and expected returns (right panel). The units are annualized percentage points. The horizon is the 6-month spot rate, 6 months from now. The sample is the longest available for each exchange in the full sample.

| | Risk Premia | | | | Expected Returns | | | |
|---|---|---|---|---|---|---|---|---|
| | Spot $\tilde{\mu}_{t+6}^{(6)}$ | | Forward $\tilde{f}_t^{6,6}$ | | Spot $\tilde{\mu}_{t+6}^{(6)}$ | | Forward $f_t^{6,6}$ | |
| | Mean | StDev | Mean | StDev | Mean | StDev | Mean | StDev |
| **North America** | | | | | | | | |
| USA | 2.17 | 1.40 | 2.15 | 0.99 | 5.04 | 2.41 | 5.44 | 2.32 |
| **Europe** | | | | | | | | |
| BEL | 2.42 | 2.07 | 2.56 | 2.22 | 3.59 | 2.82 | 4.13 | 2.79 |
| CHE | 1.96 | 1.34 | 1.88 | 0.80 | 2.26 | 1.85 | 2.60 | 1.50 |
| DEU | 2.85 | 1.86 | 2.63 | 1.07 | 4.10 | 2.74 | 4.27 | 2.12 |
| ESP | 3.37 | 1.83 | 2.89 | 1.17 | 4.19 | 2.73 | 4.19 | 2.19 |
| FIN | 2.79 | 2.21 | 2.38 | 1.85 | 4.03 | 2.85 | 4.02 | 2.65 |
| FRA | 2.57 | 1.56 | 2.44 | 1.04 | 3.71 | 2.42 | 3.97 | 2.07 |
| GBR | 2.21 | 1.51 | 2.12 | 1.00 | 4.33 | 2.59 | 4.76 | 2.13 |
| ITA | 3.60 | 1.67 | 3.17 | 1.35 | 4.39 | 2.40 | 4.42 | 2.23 |
| NLD | 2.85 | 2.18 | 2.43 | 1.26 | 3.93 | 3.20 | 3.95 | 2.40 |
| SWE | 2.79 | 1.80 | 2.44 | 1.41 | 3.79 | 2.83 | 3.77 | 2.68 |
| **Pan-Europe** | | | | | | | | |
| SX5E | 2.89 | 1.83 | 2.65 | 1.08 | 4.14 | 2.69 | 4.29 | 2.10 |
| SX5P | 2.23 | 1.62 | 2.11 | 1.48 | 3.47 | 2.64 | 3.75 | 2.51 |
| SXXP | 2.14 | 1.63 | 2.05 | 1.53 | 3.12 | 2.65 | 3.44 | 2.57 |
| **Asia-Pacific** | | | | | | | | |
| AUS | 1.97 | 1.39 | 1.84 | 1.20 | 5.65 | 2.65 | 5.95 | 2.39 |
| CHN | 4.24 | 4.01 | 3.90 | 3.29 | 5.61 | 4.42 | 5.92 | 3.64 |
| HKG | 2.98 | 2.56 | 2.85 | 1.93 | 4.35 | 2.98 | 4.86 | 2.26 |
| JPN | 2.93 | 2.20 | 2.60 | 1.57 | 3.21 | 2.35 | 3.15 | 1.76 |
| KOR | 2.23 | 2.16 | 2.14 | 1.85 | 5.13 | 3.02 | 5.40 | 2.95 |
| TWN | 2.39 | 1.90 | 2.36 | 1.45 | 3.37 | 2.11 | 3.84 | 1.70 |

**Table A3**
**Alternative Measures**

This table reports regression estimates with alternative measures for option-based risk premia (Panel A) and expected returns (Panel B). See Appendix B.3 for more details. The first three subpanels report estimates from panel regressions in the main sample. The last subpanel reports estimates from time-series regressions in the U.S. sample. Mincer-Zarnowitz regressions test $H_0 : \beta_1 = 1$, as in Table 2. The average forecast error tests $H_0 : \bar{\varepsilon}_t = 0$, as in Table 4. Error-predictability regressions test $H_0 : \beta_1 = 0$, as in Table 5. The horizon is the 6-month spot rate, 6 months from now. The units are annualized percentage points. Panel regressions, in the main sample, include exchange fixed effects, compute a within $R^2$, and report standard errors clustered by exchange and date. This sample is the longest available for each exchange. Time-series regressions, in the U.S. sample, report Newey-West standard errors with lags selected following Lazarus et al. (2018) and fixed-$b$ p-values. This sample is from January 1990 to June 2021.

| | Panel A. Risk Premia $\tilde{\mu}_{t+6}^{(6)}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\tilde{\varepsilon}_t$ | $se(\tilde{\varepsilon}_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **Alternative Integration Bounds** | | | | | | | | | | | | |
| Truncation: $0.65 \leq K/P \leq 1.35$ | 0.78 | 0.091 | ** | 0.18 | 0.34 | 0.094 | *** | -0.019 | 0.039 | | 0.00 | 2139 |
| Truncation: $0.55 \leq K/P \leq 1.45$ | 0.68 | 0.074 | *** | 0.17 | 0.26 | 0.097 | ** | -0.082 | 0.041 | * | 0.01 | 2137 |
| Truncation: $0.45 \leq K/P \leq 1.55$ | 0.63 | 0.065 | *** | 0.16 | 0.22 | 0.099 | * | -0.12 | 0.042 | ** | 0.02 | 2140 |
| Truncation: $0.35 \leq K/P \leq 1.65$ | 0.59 | 0.059 | *** | 0.15 | 0.20 | 0.10 | * | -0.15 | 0.044 | *** | 0.03 | 2138 |
| Observable Moneyness | 0.56 | 0.053 | *** | 0.15 | 0.19 | 0.10 | * | -0.17 | 0.043 | *** | 0.04 | 2140 |
| Extrapolation: Static Moneyness | 0.56 | 0.056 | *** | 0.15 | 0.14 | 0.10 | | -0.15 | 0.041 | *** | 0.04 | 2244 |
| Extrapolation: Dynamic Moneyness | 0.56 | 0.055 | *** | 0.15 | 0.16 | 0.11 | | -0.17 | 0.046 | *** | 0.03 | 2241 |
| Extrapolation: Baseline | 0.56 | 0.055 | *** | 0.15 | 0.17 | 0.11 | | -0.16 | 0.047 | *** | 0.03 | 2227 |
| **Alternative Liquidity Filters** | | | | | | | | | | | | |
| Outliers | 0.60 | 0.055 | *** | 0.17 | 0.18 | 0.098 | | -0.20 | 0.050 | *** | 0.05 | 2241 |
| Open Interest: After 199601 | 0.52 | 0.057 | *** | 0.14 | 0.16 | 0.11 | | -0.18 | 0.045 | *** | 0.04 | 2033 |
| Outliers and Open Interest: After 199601 | 0.56 | 0.051 | *** | 0.16 | 0.19 | 0.097 | * | -0.21 | 0.050 | *** | 0.06 | 2040 |
| **Alternative Surfaces** | | | | | | | | | | | | |
| Volatility Surface: After 199601 | 0.57 | 0.051 | *** | 0.17 | 0.087 | 0.095 | | -0.21 | 0.053 | *** | 0.06 | 2163 |
| SVI Surface: U.S. and SX5E | 0.59 | 0.047 | * | 0.17 | 0.051 | 0.11 | | -0.19 | 0.039 | | 0.04 | 609 |
| **Alternative Prices** | | | | | | | | | | | | |
| Bid-Ask Midpoint: U.S. Only | 0.67 | 0.096 | *** | 0.22 | 0.021 | 0.15 | | -0.17 | 0.066 | ** | 0.03 | 378 |
| Bid Prices: U.S. Only | 0.64 | 0.099 | *** | 0.21 | 0.034 | 0.14 | | -0.15 | 0.077 | ** | 0.03 | 378 |
| Ask Prices: U.S. Only | 0.66 | 0.089 | *** | 0.23 | 0.0051 | 0.15 | | -0.18 | 0.060 | *** | 0.04 | 378 |

(Continued on the next page)

**Table A3**
**Alternative Measures (Continued)**

| | Panel B. Expected Returns $\mu^{(6)}_{t+6}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\varepsilon_t$ | $se(\varepsilon_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **Alternative Integration Bounds** | | | | | | | | | | | | |
| Truncation: $0.65 \leq {}^{K}/_{P} \leq 1.35$ | 1.02 | 0.053 | | 0.71 | -0.12 | 0.094 | | -0.18 | 0.043 | *** | 0.04 | 2139 |
| Truncation: $0.55 \leq {}^{K}/_{P} \leq 1.45$ | 0.99 | 0.054 | | 0.67 | -0.19 | 0.097 | * | -0.23 | 0.044 | *** | 0.07 | 2137 |
| Truncation: $0.45 \leq {}^{K}/_{P} \leq 1.55$ | 0.96 | 0.055 | | 0.64 | -0.23 | 0.099 | ** | -0.26 | 0.045 | *** | 0.09 | 2140 |
| Truncation: $0.35 \leq {}^{K}/_{P} \leq 1.65$ | 0.94 | 0.056 | | 0.63 | -0.25 | 0.10 | ** | -0.29 | 0.046 | *** | 0.10 | 2138 |
| Observable Moneyness | 0.93 | 0.058 | | 0.61 | -0.26 | 0.10 | ** | -0.31 | 0.046 | *** | 0.12 | 2140 |
| Extrapolation: Static Moneyness | 0.92 | 0.060 | | 0.60 | -0.31 | 0.100 | ** | -0.26 | 0.039 | *** | 0.12 | 2244 |
| Extrapolation: Dynamic Moneyness | 0.91 | 0.061 | | 0.59 | -0.29 | 0.10 | ** | -0.30 | 0.047 | *** | 0.11 | 2241 |
| Extrapolation: Baseline | 0.91 | 0.061 | | 0.59 | -0.28 | 0.10 | ** | -0.29 | 0.047 | *** | 0.10 | 2227 |
| **Alternative Liquidity Filters** | | | | | | | | | | | | |
| Outliers | 0.92 | 0.062 | | 0.62 | -0.27 | 0.098 | ** | -0.34 | 0.050 | *** | 0.15 | 2241 |
| Open Interest: After 199601 | 0.91 | 0.062 | | 0.59 | -0.26 | 0.10 | ** | -0.31 | 0.043 | *** | 0.12 | 2033 |
| Outliers and Open Interest: After 199601 | 0.92 | 0.064 | | 0.62 | -0.24 | 0.096 | ** | -0.35 | 0.048 | *** | 0.16 | 2040 |
| **Alternative Surfaces** | | | | | | | | | | | | |
| Volatility Surface: After 199601 | 0.93 | 0.065 | | 0.63 | -0.34 | 0.098 | *** | -0.36 | 0.052 | *** | 0.16 | 2163 |
| SVI Surface: U.S. and SX5E | 0.89 | 0.048 | | 0.65 | -0.36 | 0.11 | | -0.28 | 0.049 | | 0.10 | 609 |
| **Alternative Prices** | | | | | | | | | | | | |
| Bid-Ask Midpoint: U.S. Only | 0.88 | 0.072 | | 0.71 | -0.40 | 0.17 | ** | -0.20 | 0.090 | ** | 0.04 | 378 |
| Bid Prices: U.S. Only | 0.87 | 0.070 | * | 0.73 | -0.38 | 0.17 | ** | -0.18 | 0.11 | * | 0.04 | 378 |
| Ask Prices: U.S. Only | 0.87 | 0.076 | | 0.69 | -0.41 | 0.17 | ** | -0.21 | 0.077 | *** | 0.05 | 378 |

(Continued from the previous page)

## Table A4
## Coibion-Gorodnichenko Regressions

This table reports Coibion-Gorodnichenko regressions of future realized forecast errors on current forecast revisions for option-based risk premia (left panel) and expected returns (right panel):

$$\tilde{\varepsilon}^{m}_{i,t+n} = \beta_0 + \beta_1 \left( \tilde{f}^{(n,m)}_{i,t} - \tilde{f}^{(n+h,m)}_{i,t-h} \right) + e_{i,t+n}$$

For risk premia, the realized spot rate is the future expectation of the $m$-month equity premium, the forward rate is the current expectation of the same risk premium, and the forecast error is the realized spot rate minus the forward rate. These expectations are analogously defined for expected returns. The units are annualized percentage points. All regressions include exchange fixed effects and compute a within $R^2$. Standard errors are clustered by exchange and date. The sample is the longest available for each exchange in the main sample.

| | | | | Risk Premia $\tilde{\mu}^{(m)}_{t+n}$ | | | | Expected Returns $\mu^{(m)}_{t+n}$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **Short-Horizon Forecast Revisions** | | | | | | | | | | | | |
| $h = 1$-Month Revision | $n+m=4$ | $n=3$ | $m=1$ | -0.20 | 0.11 | * | 0.01 | -0.23 | 0.13 | * | 0.01 | 2214 |
| $h = 1$-Month Revision | $n+m=5$ | $n=4$ | $m=1$ | -0.27 | 0.11 | ** | 0.01 | -0.27 | 0.13 | * | 0.01 | 2217 |
| $h = 2$-Month Revision | $n+m=4$ | $n=3$ | $m=1$ | -0.22 | 0.081 | ** | 0.01 | -0.23 | 0.11 | * | 0.01 | 2205 |
| $h = 3$-Month Revision | $n+m=6$ | $n=3$ | $m=3$ | -0.055 | 0.056 | | 0.00 | -0.067 | 0.094 | | 0.00 | 2215 |
| $h = 3$-Month Revision | $n+m=9$ | $n=6$ | $m=3$ | -0.24 | 0.12 | * | 0.01 | 0.033 | 0.11 | | 0.00 | 2186 |
| **Long-Horizon Forecast Revisions** | | | | | | | | | | | | |
| $h = 4$-Month Revision | $n+m=5$ | $n=2$ | $m=3$ | -0.081 | 0.053 | | 0.00 | -0.086 | 0.079 | | 0.01 | 2223 |
| $h = 5$-Month Revision | $n+m=4$ | $n=1$ | $m=3$ | -0.051 | 0.053 | | 0.00 | -0.050 | 0.064 | | 0.00 | 2213 |
| $h = 6$-Month Revision | $n+m=6$ | $n=3$ | $m=3$ | -0.13 | 0.055 | ** | 0.01 | -0.031 | 0.063 | | 0.00 | 2183 |
| $h = 7$-Month Revision | $n+m=5$ | $n=2$ | $m=3$ | -0.12 | 0.040 | ** | 0.02 | -0.065 | 0.053 | | 0.00 | 2191 |
| $h = 8$-Month Revision | $n+m=4$ | $n=1$ | $m=3$ | -0.082 | 0.034 | ** | 0.01 | -0.056 | 0.044 | | 0.01 | 2181 |

## Table A5
## Power Utility Regressions

This table reports regression estimates from the standpoint of an unconstrained power utility investor fully invested in the market for option-based risk premia (Panel A) and expected returns (Panel B). See Section 4.1.5 and Appendix C.2 for more details. Mincer-Zarnowitz regressions test $H_0 : \beta_1 = 1$, as in Table 2. The average forecast error tests $H_0 : \bar{\varepsilon}_t = 0$, as in Table 4. Error-predictability regressions test $H_0 : \beta_1 = 0$, as in Table 5. The horizon is the 6-month spot rate, 6 months from now. The units are annualized percentage points. Panel regressions, in the main sample, include exchange fixed effects, compute a within $R^2$, and report standard errors clustered by exchange and date. This sample is the longest available for each exchange. Time-series regressions, in the U.S. sample, report Newey-West standard errors with lags selected following Lazarus et al. (2018) and fixed-$b$ p-values. This sample is from January 1990 to June 2021.

| | Panel A. Risk Premia $\tilde{\mu}_{t+6}^{(6)}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\tilde{\varepsilon}_t$ | $se(\tilde{\varepsilon}_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **Main Sample** | | | | | | | | | | | | |
| $\gamma = 0.75$ | 0.51 | 0.059 | *** | 0.13 | 0.045 | 0.057 | | -0.19 | 0.045 | *** | 0.04 | 2224 |
| $\gamma = 1.00$ | 0.56 | 0.055 | *** | 0.15 | 0.17 | 0.11 | | -0.16 | 0.046 | *** | 0.03 | 2220 |
| $\gamma = 1.25$ | 0.60 | 0.057 | *** | 0.15 | 0.36 | 0.15 | ** | -0.13 | 0.050 | ** | 0.02 | 2215 |
| $\gamma = 1.50$ | 0.62 | 0.062 | *** | 0.16 | 0.59 | 0.20 | ** | -0.10 | 0.054 | * | 0.01 | 2206 |
| $\gamma = 2.00$ | 0.64 | 0.075 | *** | 0.15 | 1.14 | 0.29 | *** | -0.044 | 0.057 | | 0.00 | 2181 |
| **U.S. Sample** | | | | | | | | | | | | |
| $\gamma = 0.75$ | 0.61 | 0.094 | *** | 0.21 | -0.022 | 0.083 | | -0.20 | 0.069 | *** | 0.05 | 378 |
| $\gamma = 1.00$ | 0.67 | 0.096 | *** | 0.22 | 0.021 | 0.15 | | -0.17 | 0.066 | ** | 0.03 | 378 |
| $\gamma = 1.25$ | 0.72 | 0.098 | ** | 0.23 | 0.12 | 0.20 | | -0.13 | 0.064 | ** | 0.02 | 378 |
| $\gamma = 1.50$ | 0.76 | 0.100 | ** | 0.24 | 0.25 | 0.26 | | -0.099 | 0.062 | | 0.01 | 378 |
| $\gamma = 2.00$ | 0.85 | 0.10 | | 0.26 | 0.57 | 0.35 | | -0.048 | 0.059 | | 0.00 | 378 |
| $\gamma = 2.50$ | 0.91 | 0.10 | | 0.27 | 0.94 | 0.44 | ** | -0.0087 | 0.057 | | -0.00 | 378 |
| $\gamma = 3.00$ | 0.97 | 0.10 | | 0.28 | 1.32 | 0.52 | ** | 0.022 | 0.056 | | -0.00 | 378 |

| | Panel B. Expected Returns $\mu_{t+6}^{(6)}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\varepsilon_t$ | $se(\varepsilon_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **Main Sample** | | | | | | | | | | | | |
| $\gamma = 0.75$ | 0.93 | 0.042 | | 0.75 | -0.40 | 0.061 | *** | -0.42 | 0.056 | *** | 0.17 | 2224 |
| $\gamma = 1.00$ | 0.91 | 0.061 | | 0.59 | -0.28 | 0.10 | ** | -0.30 | 0.046 | *** | 0.11 | 2220 |
| $\gamma = 1.25$ | 0.90 | 0.075 | | 0.50 | -0.084 | 0.15 | | -0.22 | 0.048 | *** | 0.07 | 2215 |
| $\gamma = 1.50$ | 0.90 | 0.088 | | 0.43 | 0.15 | 0.19 | | -0.17 | 0.052 | *** | 0.04 | 2206 |
| $\gamma = 2.00$ | 0.88 | 0.11 | | 0.36 | 0.69 | 0.28 | ** | -0.093 | 0.057 | | 0.01 | 2181 |
| **U.S. Sample** | | | | | | | | | | | | |
| $\gamma = 0.75$ | 0.89 | 0.061 | * | 0.84 | -0.44 | 0.14 | *** | -0.24 | 0.13 | * | 0.04 | 378 |
| $\gamma = 1.00$ | 0.88 | 0.072 | | 0.71 | -0.40 | 0.17 | ** | -0.20 | 0.090 | ** | 0.04 | 378 |
| $\gamma = 1.25$ | 0.87 | 0.082 | | 0.61 | -0.30 | 0.21 | | -0.15 | 0.077 | ** | 0.03 | 378 |
| $\gamma = 1.50$ | 0.87 | 0.089 | | 0.53 | -0.17 | 0.25 | | -0.12 | 0.070 | * | 0.02 | 378 |
| $\gamma = 2.00$ | 0.90 | 0.096 | | 0.45 | 0.15 | 0.34 | | -0.066 | 0.063 | | 0.00 | 378 |
| $\gamma = 2.50$ | 0.93 | 0.098 | | 0.41 | 0.52 | 0.42 | | -0.024 | 0.059 | | -0.00 | 378 |
| $\gamma = 3.00$ | 0.96 | 0.098 | | 0.39 | 0.90 | 0.50 | * | 0.0077 | 0.056 | | -0.00 | 378 |

## Table A6
## Long-Horizon Forecast Errors

This table reports estimates of the predicted forecast error decay for the Euro Stoxx 50. The decay $\phi_t^{(n,m)}$ parameter follows the expected decay specification from De la O and Myers (2021):

$$\mathbb{E}_t\left[\varepsilon_{t+n}^{(m)}\right] = \phi_t^{(n,m)}\,\mathbb{E}_t\left[\varepsilon_{t+12}^{(12)}\right]$$

The estimate is the median by horizon:

$$\phi^{(n,m)} = median\left\{\left|\phi_t^{(n,m)}\right|\right\}$$

The predicted forecast error is from a time-series regression of future realized forecast errors on current forward rates: the predictor is the $n-12\times 12$-month forward rate for $n \geq 24$ and the $6\times 6$-month forward rate for $n = 12$. The sample is from 09/2005 to 09/2014.

| | $n$-months | | | | | | |
|---|---|---|---|---|---|---|---|
| $m$-months | 12 | 24 | 36 | 48 | 60 | 72 | 84 |
| 12 | 1.00 | 2.13 | 1.88 | 0.73 | 0.89 | 1.23 | 1.05 |
| 24 | 1.00 | 2.13 | 1.94 | 0.90 | 0.88 | 1.37 | |
| 36 | 1.00 | 2.09 | 1.98 | 0.95 | 0.98 | | |
| 48 | 1.00 | 2.13 | 1.99 | 1.08 | | | |
| 60 | 1.00 | 2.09 | 1.91 | | | | |
| 72 | 1.00 | 2.07 | | | | | |
| 84 | 1.00 | | | | | | |

## Table A7
## Forecast Errors and Monetary Policy Shocks

The table reports the comovement between forecast errors and monetary policy shocks in the U.S. (Panel A) and the Eurozone (Panel B). See Appendix C.4 for more details. For option-based risk premia, the $R^2$ is from a time-series regression of contemporaneous forecast errors on monetary policy shocks

$$\tilde{\varepsilon}_{t+6}^{(6)} = \beta_0 + \beta_1 \left( \sum_{h=1}^{6} \text{MPS}_{t+h} \right) + e_{t+6}$$

and the correlation is between the same two variables. These expectations are analogously defined for the risk-free rate. The horizon is the 6-month spot rate, 6 months from now. The units are annualized percentage points. U.S. forecast errors are for the S&P 500, Eurozone the Euro Stoxx 50. BK monetary policy shocks are obtained from Ken Kuttner's website, GSS and NS are obtained via Acosta (2023) from Miguel Acosta's website, and LVVW are obtained from Andrea Vedolin's website.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Panel A. U.S. Monetary Policy Shocks | | | | | | |
| | | | | Correlation $\rho$ | | Explained Variation $R^2$ | |
| | Start | End | Length | Risk-Free | Risk Premia | Risk-Free | Risk Premia |
| **Bernanke-Kuttner:** BK | | | | | | | |
| Fed Funds Rate Change | 199402 | 201812 | 299 | 0.64 | -0.31 | 0.40 | 0.09 |
| Fed Funds Rate Surprise | 199402 | 201812 | 299 | 0.12 | -0.26 | 0.01 | 0.07 |
| **Gurkaynak-Sack-Swanson:** GSS | | | | | | | |
| Target Shock | 199905 | 202106 | 266 | 0.21 | -0.18 | 0.05 | 0.03 |
| Path Shock | 199905 | 202106 | 266 | 0.51 | -0.25 | 0.26 | 0.06 |
| **Nakamura-Steinsson:** NS | | | | | | | |
| Fed Funds Rate Shock | 199905 | 202106 | 266 | 0.17 | -0.18 | 0.03 | 0.03 |
| Policy News Shock | 199905 | 202106 | 266 | 0.56 | -0.32 | 0.32 | 0.10 |
| | Panel B. Eurozone Monetary Policy Shocks | | | | | | |
| | | | | Correlation $\rho$ | | Explained Variation $R^2$ | |
| | Start | End | Length | Risk-Free | Risk Premia | Risk-Free | Risk Premia |
| **Leombroni-Vedolin-Venter-Whelan:** LVVW | | | | | | | |
| Target Shock | 200201 | 202006 | 222 | -0.30 | 0.15 | 0.09 | 0.02 |
| Forward Guidance Shock | 200201 | 202006 | 222 | 0.23 | -0.36 | 0.05 | 0.13 |
| Risk Premium Shock | 200201 | 202006 | 222 | 0.53 | -0.28 | 0.28 | 0.08 |

# Table A8
# Alternative Samples

This table reports regression estimates in alternative samples for option-based risk premia (Panel A) and expected returns (Panel B). See Appendix C.5 and Table A1 for more details. Mincer-Zarnowitz regressions test $H_0 : \beta_1 = 1$, as in Table 2. The average forecast error tests $H_0 : \bar{\varepsilon}_t = 0$, as in Table 4. Error-predictability regressions test $H_0 : \beta_1 = 0$, as in Table 5. The horizon is the 6-month spot rate, 6 months from now. The units are annualized percentage points. All regressions include exchange fixed effects and compute a within $R^2$. Standard errors are clustered by exchange and date. The sample is the longest available for each exchange.

| | Panel A. Risk Premia $\tilde{\mu}_{t+6}^{(6)}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\tilde{\varepsilon}_t$ | $se(\tilde{\varepsilon}_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **Baseline** | | | | | | | | | | | | |
| Main: 10 Indexes | 0.56 | 0.055 | *** | 0.15 | 0.17 | 0.11 | | -0.16 | 0.047 | *** | 0.03 | 2227 |
| Full: 20 Indexes | 0.48 | 0.053 | *** | 0.14 | 0.19 | 0.12 | | -0.26 | 0.049 | *** | 0.08 | 4199 |
| **Eurozone** | | | | | | | | | | | | |
| Main: 5 Indexes | 0.53 | 0.080 | *** | 0.12 | 0.28 | 0.13 | * | -0.15 | 0.053 | * | 0.03 | 1019 |
| Full: 8 Indexes | 0.45 | 0.10 | *** | 0.11 | 0.26 | 0.13 | * | -0.22 | 0.076 | ** | 0.05 | 1665 |
| **Europe** | | | | | | | | | | | | |
| Main: 7 Indexes | 0.55 | 0.071 | *** | 0.13 | 0.22 | 0.12 | | -0.15 | 0.049 | ** | 0.03 | 1474 |
| Full: 13 Indexes | 0.46 | 0.075 | *** | 0.13 | 0.21 | 0.12 | * | -0.22 | 0.058 | *** | 0.06 | 2696 |
| **Asia-Pacific** | | | | | | | | | | | | |
| Main: 2 Indexes | 0.54 | 0.093 | | 0.18 | 0.13 | 0.11 | | -0.20 | 0.12 | | 0.04 | 375 |
| Full: 6 Indexes | 0.48 | 0.057 | *** | 0.14 | 0.18 | 0.16 | | -0.33 | 0.064 | *** | 0.12 | 1125 |
| **Excludes U.S.** | | | | | | | | | | | | |
| Main: 9 Indexes | 0.55 | 0.056 | *** | 0.14 | 0.20 | 0.11 | | -0.16 | 0.049 | ** | 0.03 | 1849 |
| Full: 19 Indexes | 0.47 | 0.053 | *** | 0.13 | 0.20 | 0.12 | | -0.27 | 0.051 | *** | 0.08 | 3821 |
| | Panel B. Expected Returns $\mu_{t+6}^{(6)}$ | | | | | | | | | | | |
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\varepsilon_t$ | $se(\varepsilon_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **Baseline** | | | | | | | | | | | | |
| Main: 10 Indexes | 0.91 | 0.061 | | 0.59 | -0.28 | 0.10 | ** | -0.29 | 0.047 | *** | 0.10 | 2227 |
| Full: 20 Indexes | 0.79 | 0.089 | ** | 0.47 | -0.25 | 0.12 | * | -0.37 | 0.058 | *** | 0.15 | 4199 |
| **Eurozone** | | | | | | | | | | | | |
| Main: 5 Indexes | 0.92 | 0.081 | | 0.57 | -0.13 | 0.12 | | -0.30 | 0.056 | *** | 0.11 | 1019 |
| Full: 8 Indexes | 0.83 | 0.11 | | 0.49 | -0.15 | 0.13 | | -0.35 | 0.080 | *** | 0.14 | 1665 |
| **Europe** | | | | | | | | | | | | |
| Main: 7 Indexes | 0.94 | 0.077 | | 0.59 | -0.21 | 0.11 | | -0.30 | 0.052 | *** | 0.12 | 1474 |
| Full: 13 Indexes | 0.84 | 0.089 | * | 0.53 | -0.20 | 0.12 | | -0.35 | 0.064 | *** | 0.15 | 2696 |
| **Asia-Pacific** | | | | | | | | | | | | |
| Main: 2 Indexes | 0.86 | 0.092 | | 0.51 | -0.40 | 0.14 | | -0.31 | 0.10 | | 0.10 | 375 |
| Full: 6 Indexes | 0.67 | 0.12 | ** | 0.32 | -0.29 | 0.17 | | -0.42 | 0.072 | *** | 0.17 | 1125 |
| **Excludes U.S.** | | | | | | | | | | | | |
| Main: 9 Indexes | 0.92 | 0.074 | | 0.57 | -0.25 | 0.11 | * | -0.30 | 0.048 | *** | 0.11 | 1849 |
| Full: 19 Indexes | 0.78 | 0.096 | ** | 0.45 | -0.23 | 0.12 | * | -0.38 | 0.059 | *** | 0.16 | 3821 |

# Table A9
## Alternative Horizons

This table reports regression estimates at alternative horizons for option-based risk premia (Panel A) and expected returns (Panel B). See Appendix C.5 for more details. Mincer-Zarnowitz regressions test $H_0 : \beta_1 = 1$, as in Table 2. The average forecast error tests $H_0 : \bar{\varepsilon}_t = 0$, as in Table 4. Error-predictability regressions test $H_0 : \beta_1 = 0$, as in Table 5. The horizon is the $m$-month spot rate, $n$ months from now. The units are annualized percentage points. All regressions include exchange fixed effects and compute a within $R^2$. Standard errors are clustered by exchange and date. The sample is the longest available for each exchange in the main sample.

| | Panel A. Risk Premia $\tilde{\mu}_n^m$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\tilde{\varepsilon}_t$ | $se(\tilde{\varepsilon}_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **4-Month Horizon:** $n + m = 4$ | | | | | | | | | | | | |
| $n = 1$ $m = 3$ | 0.90 | 0.048 | * | 0.62 | 0.044 | 0.073 | | -0.12 | 0.040 | ** | 0.03 | 2269 |
| $n = 2$ $m = 2$ | 0.77 | 0.058 | *** | 0.35 | 0.055 | 0.11 | | -0.20 | 0.053 | *** | 0.04 | 2268 |
| $n = 3$ $m = 1$ | 0.68 | 0.065 | *** | 0.20 | 0.094 | 0.14 | | -0.24 | 0.055 | *** | 0.04 | 2235 |
| **5-Month Horizon:** $n + m = 5$ | | | | | | | | | | | | |
| $n = 1$ $m = 4$ | 0.94 | 0.043 | | 0.67 | 0.067 | 0.064 | | -0.075 | 0.033 | * | 0.02 | 2269 |
| $n = 2$ $m = 3$ | 0.83 | 0.053 | ** | 0.42 | 0.12 | 0.10 | | -0.13 | 0.043 | ** | 0.02 | 2268 |
| $n = 3$ $m = 2$ | 0.74 | 0.063 | *** | 0.25 | 0.16 | 0.13 | | -0.15 | 0.049 | ** | 0.02 | 2241 |
| $n = 4$ $m = 1$ | 0.62 | 0.078 | *** | 0.13 | 0.27 | 0.15 | | -0.19 | 0.053 | *** | 0.02 | 2236 |
| **6-Month Horizon:** $n + m = 6$ | | | | | | | | | | | | |
| $n = 1$ $m = 5$ | 0.95 | 0.037 | | 0.70 | 0.067 | 0.058 | | -0.054 | 0.029 | * | 0.01 | 2269 |
| $n = 2$ $m = 4$ | 0.86 | 0.047 | ** | 0.46 | 0.14 | 0.091 | | -0.094 | 0.036 | ** | 0.01 | 2268 |
| $n = 3$ $m = 3$ | 0.78 | 0.058 | *** | 0.30 | 0.21 | 0.12 | | -0.11 | 0.044 | ** | 0.01 | 2249 |
| $n = 4$ $m = 2$ | 0.67 | 0.072 | *** | 0.17 | 0.27 | 0.14 | * | -0.15 | 0.050 | ** | 0.02 | 2238 |
| $n = 5$ $m = 1$ | 0.57 | 0.076 | *** | 0.09 | 0.32 | 0.17 | * | -0.20 | 0.057 | *** | 0.02 | 2228 |
| **9-Month Horizon:** $n + m = 9$ | | | | | | | | | | | | |
| $n = 3$ $m = 6$ | 0.81 | 0.055 | *** | 0.39 | 0.15 | 0.087 | | -0.065 | 0.036 | | 0.01 | 2257 |
| $n = 4$ $m = 5$ | 0.73 | 0.066 | *** | 0.26 | 0.21 | 0.10 | * | -0.10 | 0.044 | ** | 0.01 | 2242 |
| $n = 5$ $m = 4$ | 0.65 | 0.071 | *** | 0.17 | 0.26 | 0.12 | * | -0.14 | 0.049 | ** | 0.02 | 2232 |
| $n = 6$ $m = 3$ | 0.55 | 0.071 | *** | 0.10 | 0.28 | 0.14 | * | -0.17 | 0.051 | *** | 0.02 | 2224 |
| **12-Month Horizon:** $n + m = 12$ | | | | | | | | | | | | |
| $n = 3$ $m = 9$ | 0.81 | 0.049 | *** | 0.44 | 0.094 | 0.070 | | -0.059 | 0.036 | | 0.01 | 2258 |
| $n = 6$ $m = 6$ | 0.56 | 0.055 | *** | 0.15 | 0.17 | 0.11 | | -0.16 | 0.047 | *** | 0.03 | 2227 |
| $n = 9$ $m = 3$ | 0.39 | 0.097 | *** | 0.06 | 0.25 | 0.15 | | -0.24 | 0.052 | *** | 0.04 | 2191 |

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## Table A9
## Alternative Horizons (Continued)

| | Panel B. Expected Returns $\mu_n^m$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\varepsilon_t$ | $se(\varepsilon_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| **4-Month Horizon:** $n+m=4$ | | | | | | | | | | | | |
| $n=1$ $m=3$ | 0.96 | 0.042 | | 0.80 | -0.074 | 0.073 | | -0.17 | 0.039 | *** | 0.06 | 2269 |
| $n=2$ $m=2$ | 0.90 | 0.057 | | 0.62 | -0.21 | 0.11 | * | -0.30 | 0.056 | *** | 0.09 | 2268 |
| $n=3$ $m=1$ | 0.89 | 0.068 | | 0.50 | -0.26 | 0.14 | * | -0.36 | 0.059 | *** | 0.08 | 2235 |
| **5-Month Horizon:** $n+m=5$ | | | | | | | | | | | | |
| $n=1$ $m=4$ | 0.99 | 0.038 | | 0.84 | -0.027 | 0.063 | | -0.12 | 0.033 | *** | 0.04 | 2269 |
| $n=2$ $m=3$ | 0.95 | 0.052 | | 0.69 | -0.080 | 0.097 | | -0.22 | 0.046 | *** | 0.06 | 2268 |
| $n=3$ $m=2$ | 0.94 | 0.063 | | 0.57 | -0.13 | 0.12 | | -0.27 | 0.053 | *** | 0.06 | 2241 |
| $n=4$ $m=1$ | 0.92 | 0.080 | | 0.45 | -0.11 | 0.14 | | -0.33 | 0.057 | *** | 0.06 | 2236 |
| **6-Month Horizon:** $n+m=6$ | | | | | | | | | | | | |
| $n=1$ $m=5$ | 0.99 | 0.035 | | 0.86 | -0.027 | 0.057 | | -0.10 | 0.029 | *** | 0.03 | 2269 |
| $n=2$ $m=4$ | 0.97 | 0.049 | | 0.73 | -0.039 | 0.086 | | -0.18 | 0.040 | *** | 0.05 | 2268 |
| $n=3$ $m=3$ | 0.97 | 0.057 | | 0.63 | -0.043 | 0.11 | | -0.22 | 0.048 | *** | 0.05 | 2249 |
| $n=4$ $m=2$ | 0.95 | 0.071 | | 0.52 | -0.082 | 0.13 | | -0.29 | 0.052 | *** | 0.06 | 2238 |
| $n=5$ $m=1$ | 0.93 | 0.082 | | 0.42 | -0.15 | 0.15 | | -0.36 | 0.059 | *** | 0.07 | 2228 |
| **9-Month Horizon:** $n+m=9$ | | | | | | | | | | | | |
| $n=3$ $m=6$ | 0.97 | 0.046 | | 0.73 | -0.075 | 0.082 | | -0.16 | 0.036 | *** | 0.05 | 2257 |
| $n=4$ $m=5$ | 0.97 | 0.055 | | 0.66 | -0.082 | 0.096 | | -0.22 | 0.040 | *** | 0.06 | 2242 |
| $n=5$ $m=4$ | 0.97 | 0.063 | | 0.59 | -0.10 | 0.11 | | -0.27 | 0.046 | *** | 0.08 | 2232 |
| $n=6$ $m=3$ | 0.94 | 0.071 | | 0.51 | -0.17 | 0.13 | | -0.31 | 0.053 | *** | 0.08 | 2224 |
| **12-Month Horizon:** $n+m=12$ | | | | | | | | | | | | |
| $n=3$ $m=9$ | 0.96 | 0.039 | | 0.78 | -0.14 | 0.067 | * | -0.15 | 0.034 | *** | 0.06 | 2258 |
| $n=6$ $m=6$ | 0.91 | 0.061 | | 0.59 | -0.28 | 0.10 | ** | -0.29 | 0.047 | *** | 0.10 | 2227 |
| $n=9$ $m=3$ | 0.81 | 0.077 | ** | 0.41 | -0.46 | 0.15 | ** | -0.41 | 0.062 | *** | 0.12 | 2191 |

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# Table A10
## Additional Robustness Checks

This table reports additional robustness checks for option-based risk premia (Panel A) and expected returns (Panel B). See Appendix C.5 for more details. Mincer-Zarnowitz regressions test $H_0 : \beta_1 = 1$, as in Table 2. The average forecast error tests $H_0 : \bar{\varepsilon}_t = 0$, as in Table 4. Error-predictability regressions test $H_0 : \beta_1 = 0$, as in Table 5. The horizon is the 6-month spot rate, 6 months from now. The units are annualized percentage points. All regressions include exchange fixed effects and compute a within $R^2$. Standard errors are clustered by exchange and date. The sample is the longest available for each exchange in the main sample.

| | Panel A. Risk Premia $\tilde{\mu}^{(6)}_{t+6}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\tilde{\varepsilon}_t$ | $se(\tilde{\varepsilon}_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| Baseline: 199001 to 202106 | 0.56 | 0.055 | *** | 0.15 | 0.17 | 0.11 | | -0.16 | 0.047 | *** | 0.03 | 2227 |
| Winsorization: 199001 to 202106 | 0.60 | 0.059 | *** | 0.19 | 0.15 | 0.093 | | -0.15 | 0.048 | ** | 0.03 | 2227 |
| Trimming: 199001 to 202106 | 0.57 | 0.056 | *** | 0.18 | 0.091 | 0.078 | | -0.10 | 0.049 | * | 0.01 | 2029 |
| Balanced Panel: 200610 to 202010 | 0.49 | 0.058 | *** | 0.12 | 0.22 | 0.13 | | -0.20 | 0.050 | *** | 0.05 | 1674 |
| First Half: 199001 to 201110 | 0.49 | 0.078 | *** | 0.11 | 0.37 | 0.19 | * | -0.25 | 0.064 | *** | 0.07 | 1113 |
| Second Half: 201111 to 202106 | 0.30 | 0.12 | *** | 0.06 | -0.024 | 0.099 | | -0.11 | 0.081 | | 0.01 | 1114 |

| | Panel B. Expected Returns $\mu^{(6)}_{t+6}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mincer-Zarnowitz | | | | Average Error | | | Error Predictability | | | | |
| | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | $\varepsilon_t$ | $se(\varepsilon_t)$ | $p$-val | $\beta_1$ | $se(\beta_1)$ | $p$-val | $R^2$ | N |
| Baseline: 199001 to 202106 | 0.91 | 0.061 | | 0.59 | -0.28 | 0.10 | ** | -0.29 | 0.047 | *** | 0.10 | 2227 |
| Winsorization: 199001 to 202106 | 0.91 | 0.048 | * | 0.65 | -0.31 | 0.092 | *** | -0.28 | 0.051 | *** | 0.11 | 2227 |
| Trimming: 199001 to 202106 | 0.90 | 0.045 | * | 0.65 | -0.33 | 0.079 | *** | -0.20 | 0.051 | *** | 0.06 | 2041 |
| Balanced Panel: 200610 to 202010 | 0.89 | 0.080 | | 0.55 | -0.28 | 0.13 | * | -0.35 | 0.048 | *** | 0.14 | 1674 |
| First Half: 199001 to 201110 | 0.78 | 0.11 | * | 0.30 | -0.14 | 0.18 | | -0.40 | 0.061 | *** | 0.18 | 1113 |
| Second Half: 201111 to 202106 | 0.43 | 0.085 | *** | 0.21 | -0.41 | 0.11 | *** | -0.19 | 0.088 | * | 0.04 | 1114 |

## Table A11
## Model Calibration: Objective Parameters

This table reports AR(3) time-series regressions for 3-month spot rates:

$$\mu_t^{(3)} = \left(1 - \sum_{j=1}^{3} \phi_j\right) \bar{\mu} + \phi_1 \, \mu_{t-1}^{(3)} + \phi_2 \, \mu_{t-2}^{(3)} + \phi_3 \, \mu_{t-3}^{(3)} + e_t$$

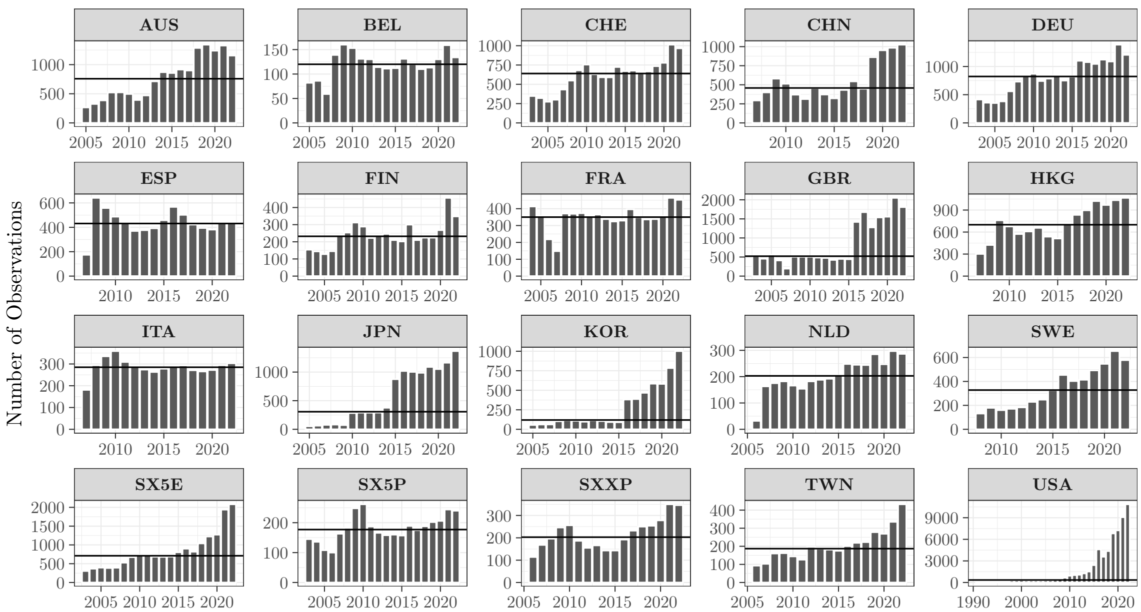
The units are annualized percentage points. Standard errors are from 10,000 Monte Carlo simulations of length $T$ months. The sample is the longest available for each exchange in the main sample.

| | AUS | CHE | DEU | ESP | FRA | GBR | HKG | ITA | SX5E | USA |
|---|---|---|---|---|---|---|---|---|---|---|
| $\phi_1$ | 0.59 | 0.78 | 0.79 | 0.76 | 0.87 | 0.90 | 0.74 | 0.66 | 0.77 | 0.94 |
| | (0.07) | (0.07) | (0.07) | (0.08) | (0.07) | (0.07) | (0.07) | (0.08) | (0.07) | (0.05) |
| $\phi_2$ | 0.02 | -0.01 | -0.06 | -0.07 | -0.14 | -0.19 | 0.16 | -0.02 | -0.03 | -0.26 |
| | (0.08) | (0.08) | (0.08) | (0.09) | (0.09) | (0.08) | (0.09) | (0.09) | (0.08) | (0.07) |
| $\phi_3$ | 0.22 | 0.05 | 0.11 | 0.09 | 0.12 | 0.14 | -0.05 | 0.11 | 0.11 | 0.18 |
| | (0.07) | (0.06) | (0.06) | (0.08) | (0.07) | (0.06) | (0.07) | (0.07) | (0.06) | (0.05) |
| $\bar{\mu}$ | 6.19 | 6.13 | 8.89 | 10.49 | 7.69 | 6.73 | 9.30 | 11.63 | 8.99 | 6.40 |
| | (1.36) | (1.00) | (1.62) | (1.48) | (1.23) | (1.21) | (2.44) | (1.27) | (1.59) | (0.89) |
| $\sigma_e$ | 3.23 | 2.86 | 3.82 | 4.41 | 2.89 | 2.89 | 5.04 | 4.31 | 3.69 | 2.56 |
| | (0.16) | (0.13) | (0.18) | (0.23) | (0.14) | (0.13) | (0.27) | (0.23) | (0.17) | (0.09) |
| $T$ | 208 | 237 | 237 | 180 | 222 | 237 | 184 | 180 | 237 | 384 |

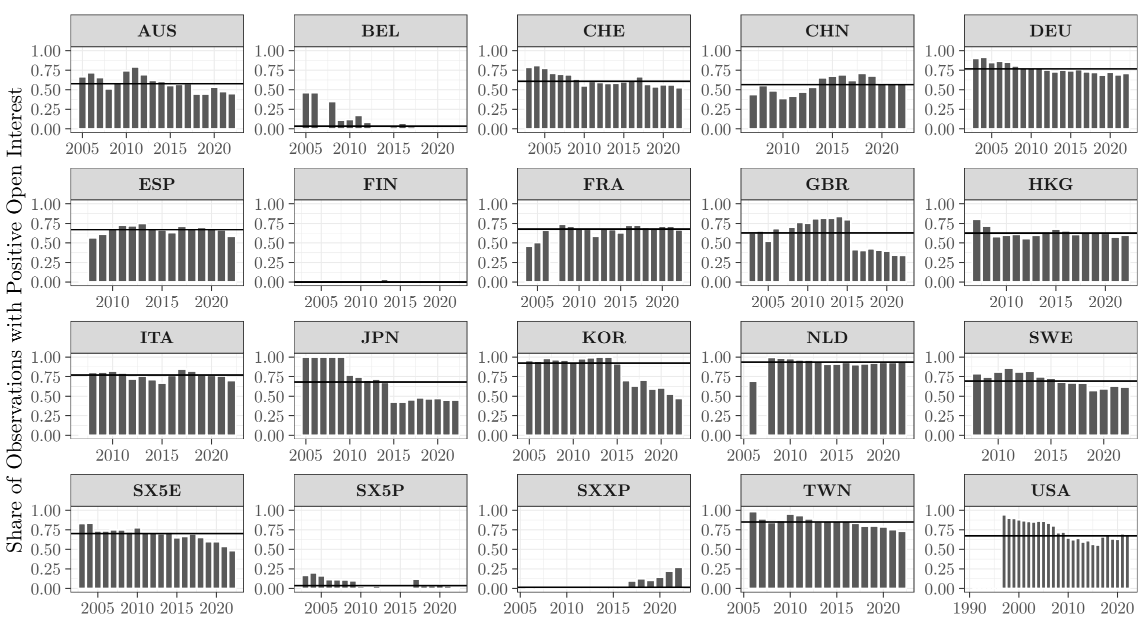
## Figure A1
## Filtered Option Prices

Panel A plots the number of options after filters. Panel B plots the share of filtered options with positive open interest. Each bar is the annual median from daily data. The black line is the full sample median from daily data. The sample is the longest available for each exchange. Option prices have maturity $30 \leq \tau \leq 365$ days. See Appendix B.1 for more details.

### Panel A. Number of Observations



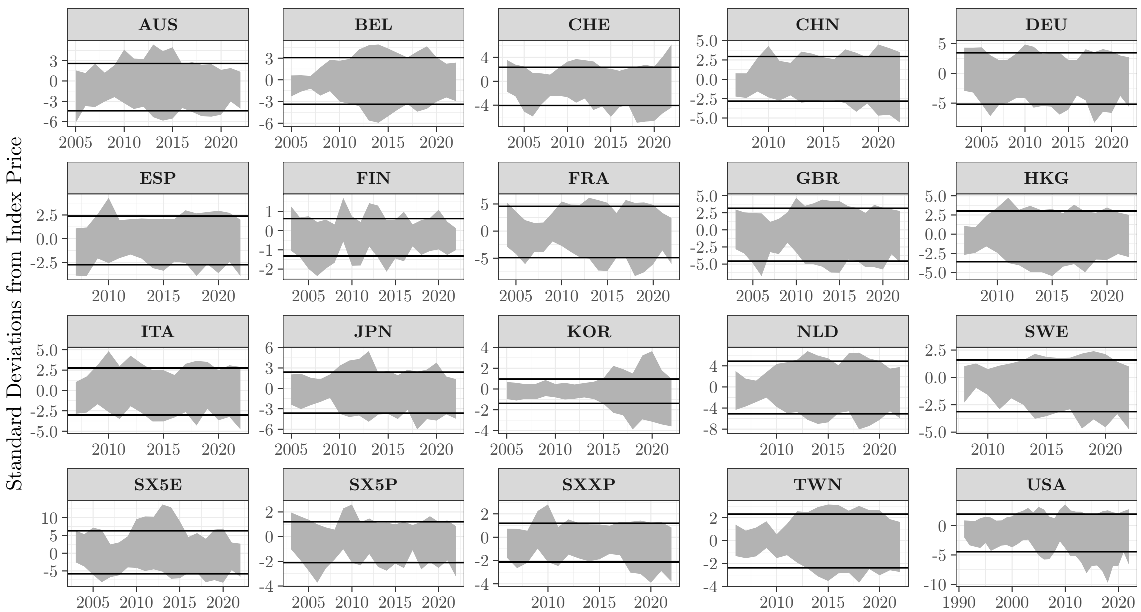

### Panel B. Positive Open Interest



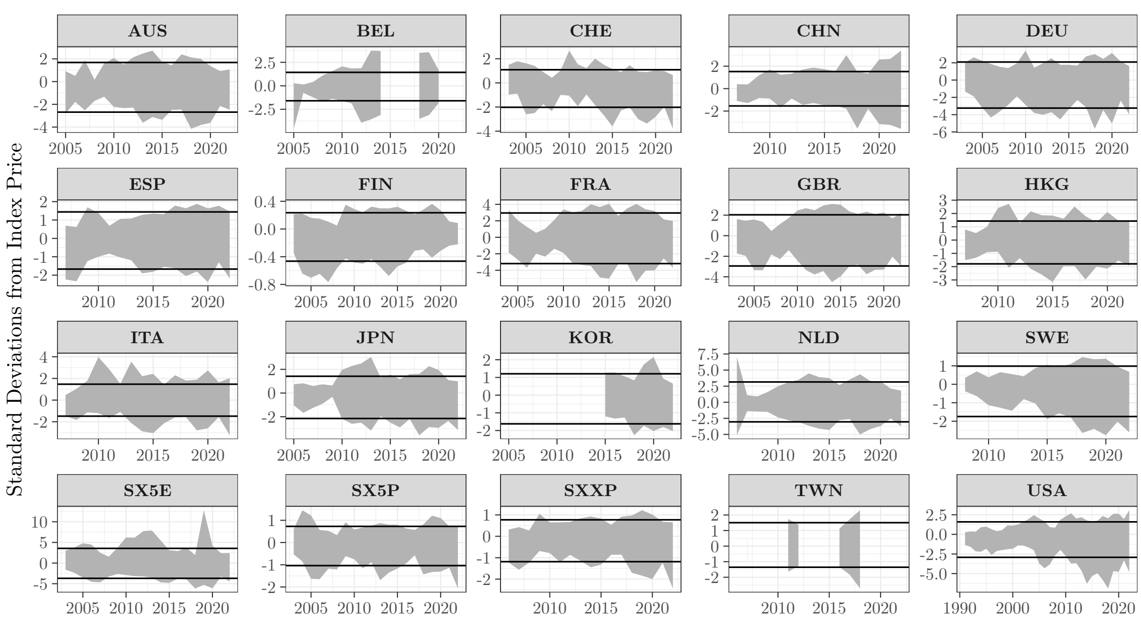
# Figure A2
# Minimum/Maximum Strike Price by Maturity

This figure plots the minimum/maximum strike price by maturity bin. The minimum/maximum is the annual median from daily data. The black line is the full sample minimum/maximum from daily data. The units are risk-neutral standard deviations from the index price. The sample is the longest available for each exchange. See Appendix B.1 for more details.

Panel A. 92 to 182 Days-to-Maturity

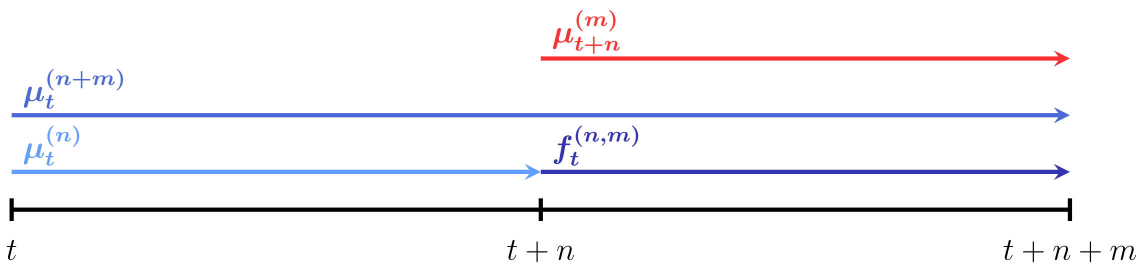



Panel B. 274 to 365 Days-to-Maturity



## Figure A3
## Timeline: Current/Realized Spot Rates and Forward Rates

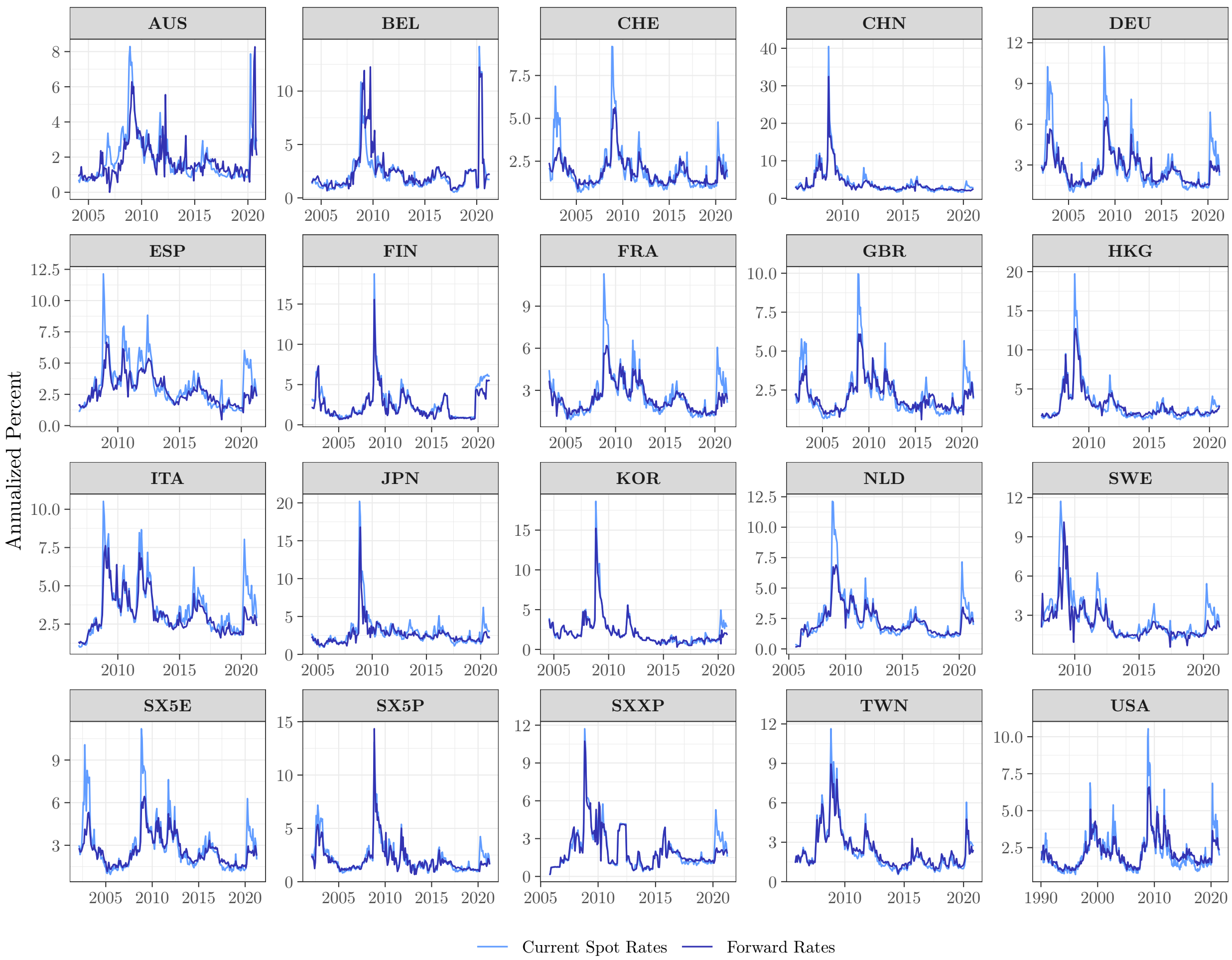
See Section 3 for more details.




- $\mu_t^{(n)} = \mathscr{L}_t^{(n)}$ is the $n$-month spot rate at time $= t$
- $\mu_t^{(n+m)} = \mathscr{L}_t^{(n+m)}$ is the $n+m$-month spot rate at time $= t$
- $f_t^{(n,m)} = \mu_t^{(n+m)} - \mu_t^{(n)}$ is the $m$-month forward rate $n$ months from time $= t$
- $\mu_{t+n}^{(m)} = \mathscr{L}_{t+n}^{(m)}$ is the $m$-month spot rate at time $= t+n$

## Figure A4
## Current Spot and Forward Rates in the Full Sample

This figure plots contemporaneous 6-month spot rates $\tilde{\mu}_t^{(6)}$ (light blue) and $6 \times 6$-month forward rates $\tilde{f}_t^{(6,6)}$ (dark blue) in the full sample. Spot and forward rates are for equity risk premia and are from option-based expectations. The sample is the longest available for each exchange.



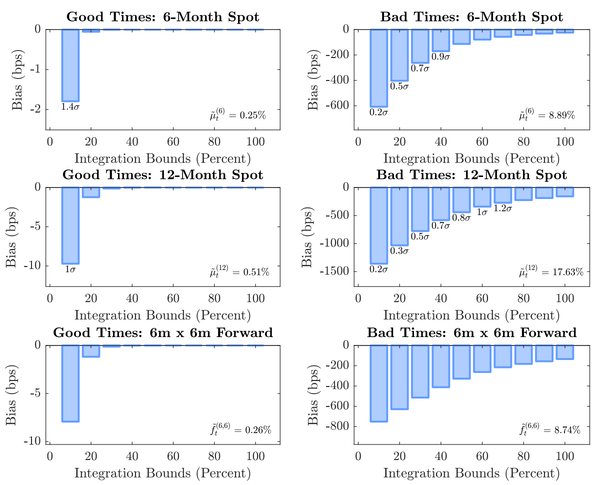
# Figure A5
# Measurement Error: Spot and Forward Rates

This figure describes truncation bias in the Black-Scholes model (left panel) and the stochastic volatility jump (SVJ) model (right panel). Integration bounds are in moneyness $K/P$ units from the index price. Bar labels are in volatility standard deviations from the index price. Black-Scholes parameters: $P_t = 100$, $r = 0.05$, $q = 0.02$. SVJ parameters under $\mathbb{Q}$ are from Bakshi, Cao, and Chen (1997):

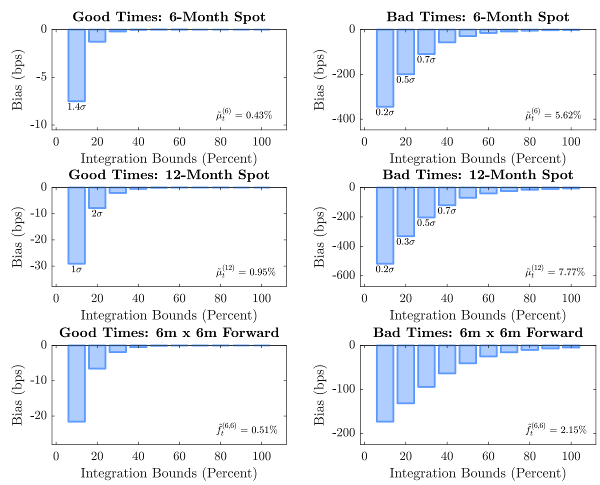
| $\theta_v$ | $\kappa_v$ | $\sigma_v$ | $\rho$ | $\mu_J$ | $\sigma_J$ | $\lambda$ |
|---|---|---|---|---|---|---|
| 0.040 | 2.030 | 0.380 | -0.570 | -0.050 | 0.070 | 0.590 |

Under Black-Scholes (SVJ), good times correspond to low volatility $IV = 10\%$ ($\sqrt{v_t} = 10\%$), bad times to high volatility $IV = 60\%$ ($\sqrt{v_t} = 60\%$). The units are non-annualized basis points. See Appendix B.2 for more details.

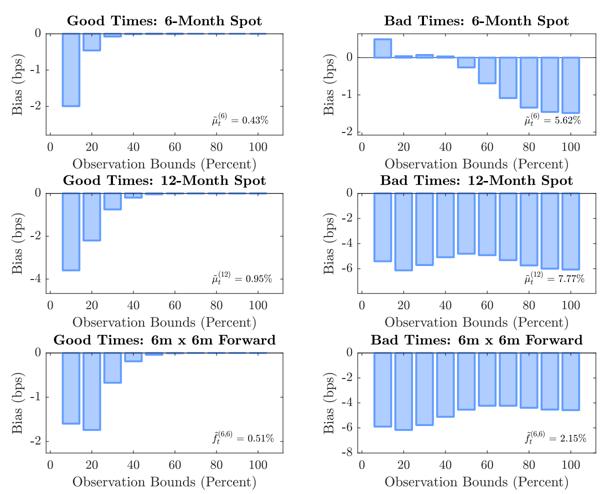
Panel A. Black-Scholes: Without Extrapolation




Panel B. Stochastic Volatility Jump: Without Extrapolation



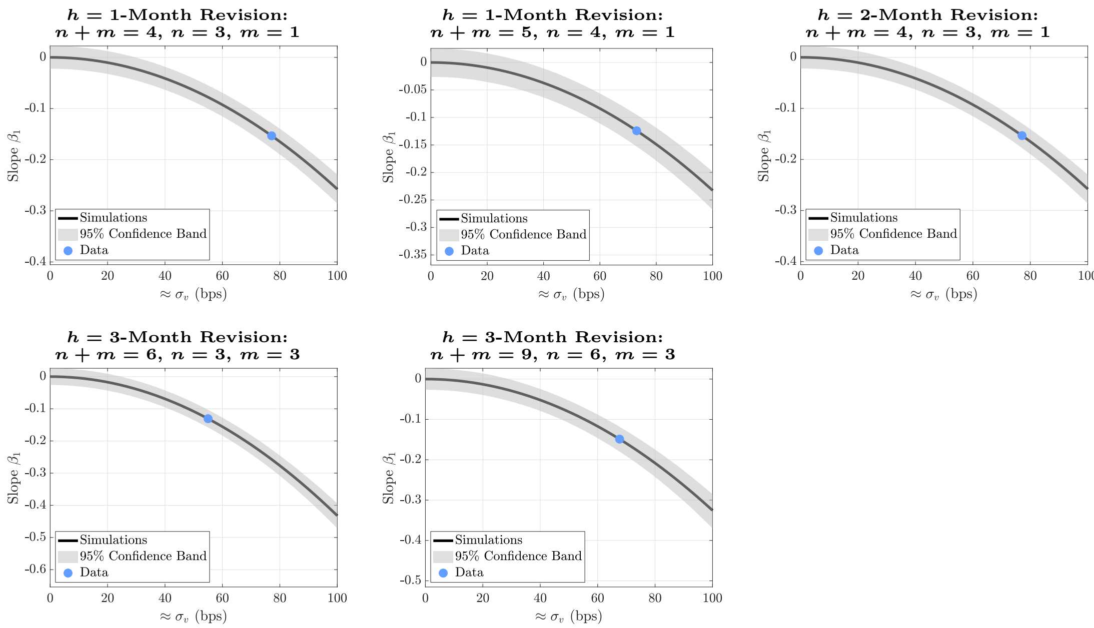

Panel C. Stochastic Volatility Jump: With Extrapolation



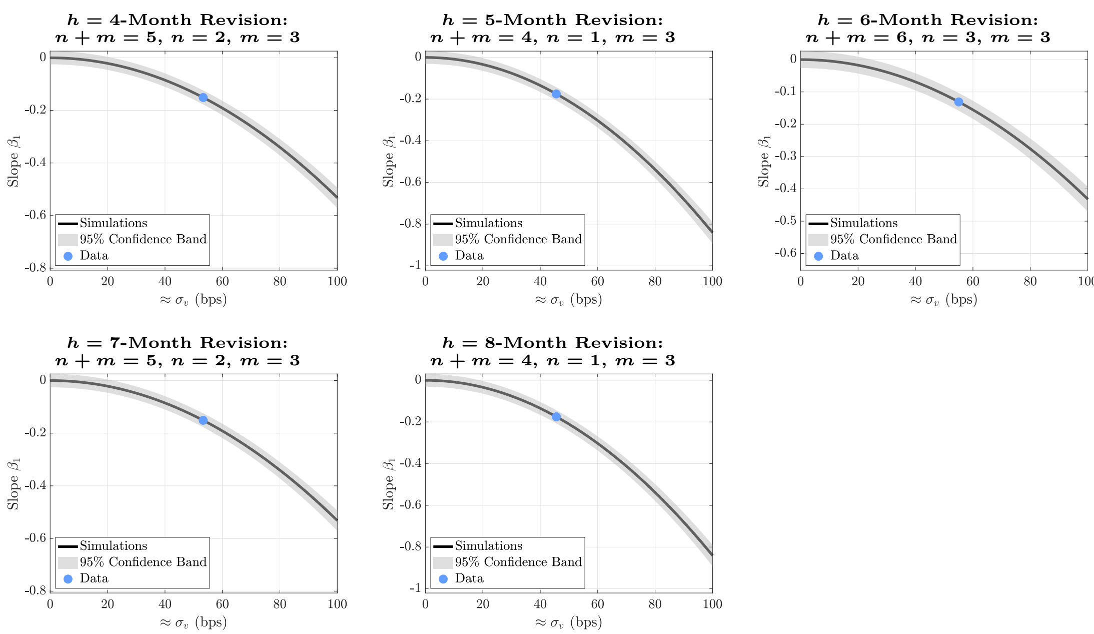
# Figure A6
# Measurement Error: Coibion-Gorodnichenko Regressions

This figure quantifies how much correlated measurement error is necessary to produce the Coibion-Gorodnichenko regression slopes in the data with monthly forecast revisions (left panel) and quarterly forecast revisions (right panel). The solid lines are the slopes in simulations. The shaded regions are 95% confidence bands in 50,000 samples. The blue circles are slopes in the data. The sample is the longest available for each exchange in the main sample. See Appendix C.1 for more details.

Panel A. Short-Horizon Forecast Revisions

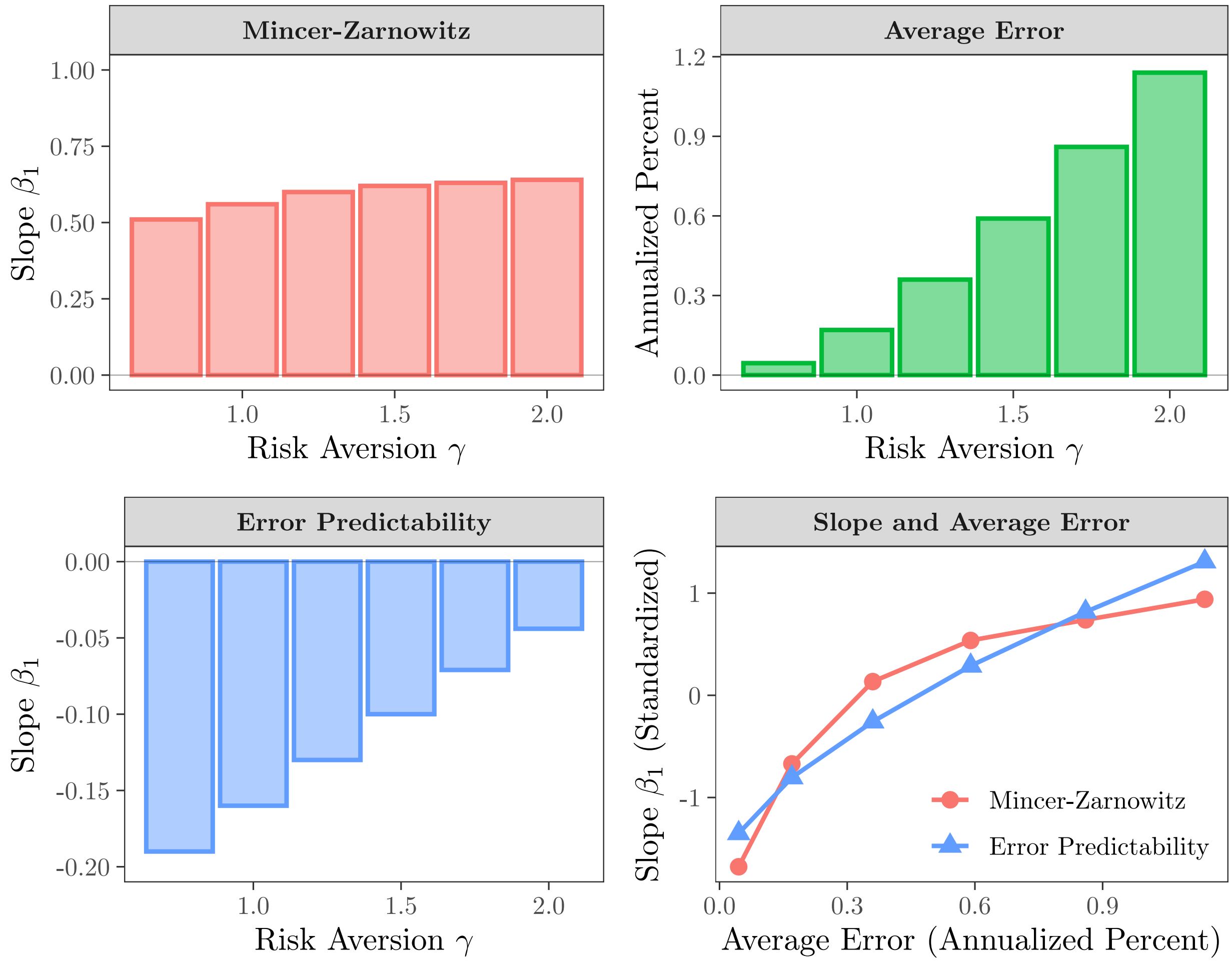



Panel B. Long-Horizon Forecast Revisions



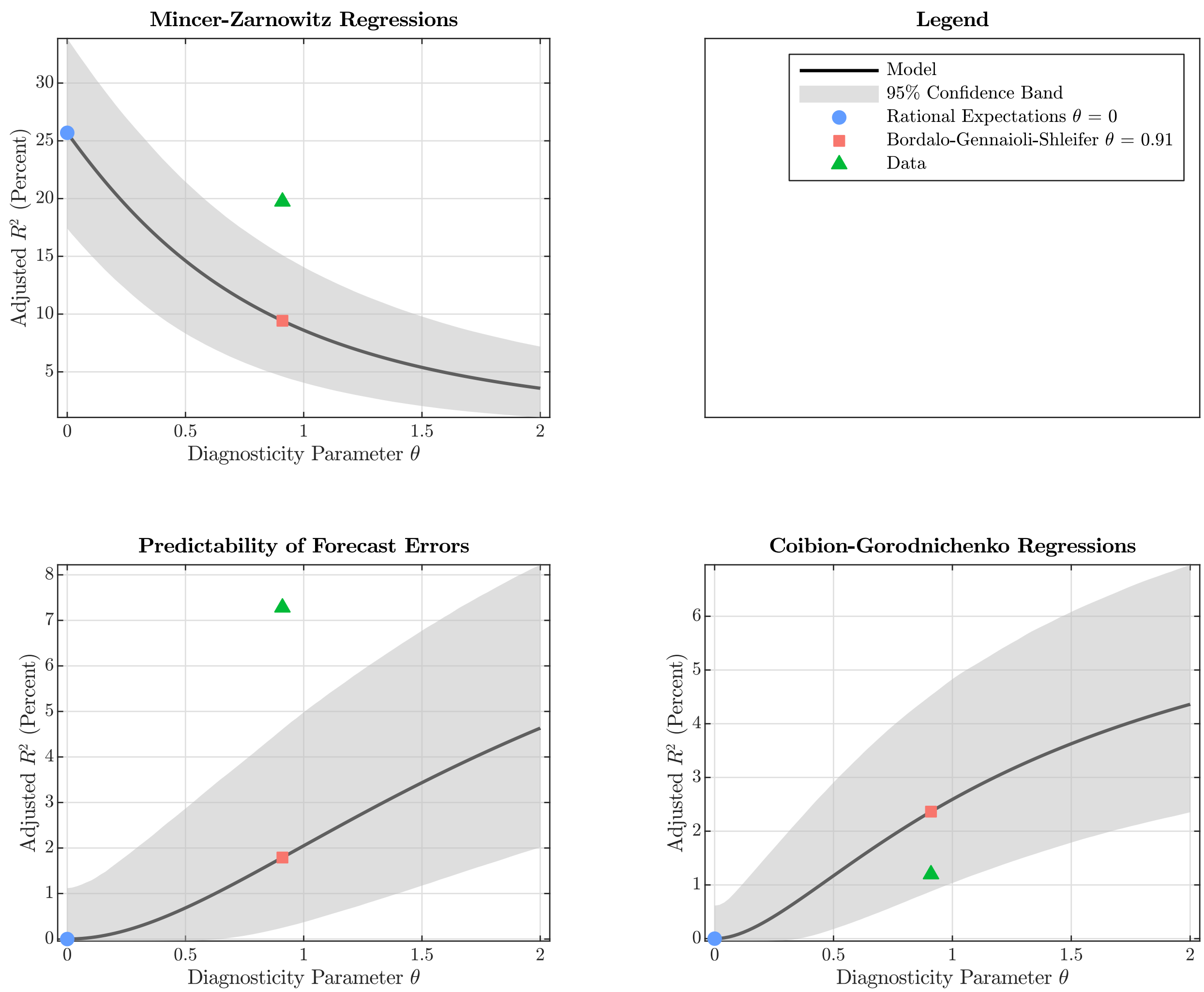
## Figure A7
## Power Utility: Regression Slopes and Average Forecast Errors

This figure reports regression slopes and average forecast errors from the standpoint of an unconstrained power utility investor fully invested in the market for option-based risk premia. See Panel A of Table A5 for more details. The sample is the longest available for each exchange in the main sample.



## Figure A8
## Model Calibration: Regression Fit

This figure reports regression $R^2$s in the calibrated model of expectation errors. The model is calibrated from the standpoint of an unconstrained log utility investor fully invested in the market. Table A11 reports the objective parameters. The solid lines are model-implied population $R^2$s in a single long sample. The shaded regions are model-implied 95% confidence bands in 10,000 short samples. The blue circles are model-implied $R^2$s under rational expectations with $\theta = 0$. The red squares are model-implied $R^2$s under diagnostic expectations with $\theta = 0.91$ from Bordalo, Gennaioli, and Shleifer (2018). The green triangles are $R^2$s in the data. The sample is the longest available for each exchange in the main sample.



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