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Extracting Growth Expectations from Financial Markets:

An Investigation into the Dividend Market Dynamics

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Abstract

Dividend futures, reflecting the economic surplus, can be used as a forecasting tool for dividend and GDP growth. Building on prior research, I broaden the scope of analysis by encompassing a range of countries and evaluate the impact of shocks such as a military conflict on dividend and GDP growth expectations. Notably, after the Russian invasion of Ukraine, dividend growth and GDP expectations declined more sharply in the Euro area and Italy than in the United Kingdom and Switzerland. The findings underscore the value of dividend futures as a tool for policymakers and market participants to obtain forward-looking insights into the anticipated economic trajectory during times of uncertainty and crisis.

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Contents

List of Figures

List of Tables

1 Introduction

The COVID-19 pandemic has underscored the need for real-time and systematic economic indicators for policymakers and market participants alike. Traditional indicators, such as industrial production and gross domestic product (GDP), may be insufficient during turbulent times due to their delayed availability. Dividend futures, which enable investors to take positions on future dividends of an index or company, offer valuable high-frequency forward-looking insights into market expectations and sentiments across a term structure.

In this paper, I build upon the approach introduced by Gormsen and Koijen (2020), who use dividend futures data to infer market forecasts of dividend and GDP changes following the coronavirus outbreak. By adapting their method, I demonstrate that the relationship between equity yields and GDP growth expectations can provide a valuable tool for investors and policymakers when assessing the state of the economy during GDP shocks across various countries, a previously unexplored area. This approach allows for more timely information, enabling policymakers to make informed decisions about appropriate policy responses during economic contractions and turmoil.

One case in point is the examination of stock price fluctuations in response to GDP shocks, such as the Russian invasion of Ukraine. For example, the Stoxx Europe 600 and FTSE 100 fell by 3.3% and 2.9%, while the Russian Moex experienced significant fluctuations, ultimately dropping by as much as 45% until trading ceased.[1] However, data derived from price changes have limitations. Market valuations fluctuate due to changes in either dividend expectations or discount rates. As Shiller (1981) points out, most variation can be attributed to the latter. Therefore, in the wake of a GDP shock, such as an invasion, increased uncertainty may escalate risk aversion, leading to a rise in investors' discount rates.

Furthermore, stock prices do not reveal the extent to which market declines stem from short-term consequences (e.g., sudden restrictions on Russian exports and imports) as opposed to medium and long-term consequences (e.g., European nations changing their energy policies). Consequently, stock prices are not optimal instruments for investigating market responses to crises. In contrast, the dividend term structure allows for an analysis of a shock's impact on future expectations over time. Moreover, dividend futures are not affected by the nonlinear relationship that affects interest rates at the zero-lower-bound (ZLB) (see e.g., Swanson and Williams (2014)).[2] Corporate bonds, which are also differentiated by maturity, could be another means of inferring changing expectations from agents in the economy. However, like government bonds, they lack the variable payoff feature of dividend futures. The uncertain payoff enables the breakdown of the n-year forward equity yield into risk premium and most importantly, the expected dividend growth, as demonstrated in Section 4.

[1] Volatility which can be compared to the Great Financial Crisis.

[2] However, the yield curve can be and has been used as a forecasting. For instance, Møller (2014) demonstrates that the curvature of the yield curve holds substantial predictive power for macroeconomic variables such as GDP.

By investigating the market's response to events like the Russian invasion of Ukraine, the onset of the COVID-19 pandemic, and other instances of financial and economic instability, this study seeks to improve our understanding of the use of dividend futures across different markets as a tool to infer expectations, how markets cope with uncertainty and how warfare is valued in financial markets.[3]

Dividend futures enable market participants to assume specific positions on future dividends, hedge dividend exposure, or exploit relative value opportunities in assets over time. These contracts are based on an underlying dividend index, which tracks the cumulative annual value of ordinary cash dividends declared by the constituents of a stock market index.[4] By taking a long position in these futures, investors commit to paying a predetermined sum in exchange for the cumulative dividends over a set year. Consequently, the fair value of a dividend futures contract represents the risk-adjusted present value of the cumulative dividends throughout this period. As mentioned, dividend futures facilitate the decomposition of stock prices into their constituent parts and offer insights into expected dividends by maturity. Since dividends can signify the surplus generated in the economy, they are closely tied to GDP, allowing for the estimation of the lower bound GDP growth expectations based on the market's outlook for dividend growth.

A plethora of research supports the connection between GDP and dividends. For instance, Ragnvid (2006) contends that a strong link exists between economic activity and dividend patterns over extended periods, suggesting that dividends exhibit mean-reverting behavior towards GDP. Similarly, Rozeff (1984) argues that the evolution of dividends over time is intimately connected to GDP growth. Moreover, Van Binsbergen et al. (2013) demonstrates correlations between the cyclical components of consumption, gross national income, and dividends are highly correlated over time, with correlations intensifying during periods of turmoil and uncertainty.

My method is inspired by Gormsen and Koijen (2020), who use data from dividend futures to quantify the market forecast of dividend and GDP changes following the outbreak of the COVID-19 pandemic. My paper diverges in three significant ways. Firstly, Gormsen and Koijen focus exclusively on the aftermath of a global pandemic that affected the economy primarily through increased mortality, implementation of non-pharmaceutical interventions, and behavioral changes in individuals and businesses. In contrast, I broaden the scope of the historical periods studied to encompass various types of shocks, such as the onset of military conflict, where the economic impact mainly originates from sanctions and their repercussions on the global supply of essential commodities like oil and gas, as well as shifts in global demand patterns.

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[3] In the macro-finance literature it is commonplace to infer the movements of for example swaps onto macroeconomic variables. See for example Gertler and Karadi (2015) and Jarociński and Karadi (2020) which both use interest rate swaps to infer monetary policy shocks.

[4] Dividend futures for specific stocks also exist, but they are not used or analyzed in this study.

Secondly, while Gormsen and Koijen's study is limited in terms of geographical focus, only including the largest global markets, my research expands the analysis to incorporate a more diverse range of countries and regions. This extension provides a more comprehensive understanding of how dividend futures can be employed to predict growth expectations across various economies and contexts. The markets included in my study are Euro Stoxx 50 (representing Europe), Nikkei 225 (Japan), FTSE 100 (United Kingdom), FTSE MIB (Italy), SMI 30 (Switzerland), and DAX (Germany).[5]

Lastly, my paper aims to critically examine Gormsen and Koijen's methodology by problematizing the theoretical boundaries and idiosyncrasies involved in forecasting GDP and dividend growth through the use of dividend futures. This effort aims to cultivate a more refined understanding of the interplay between dividend futures market dynamics, economic growth, and market responses to crises, ultimately providing valuable insights for policymakers, and financial market participants alike.

2 Dividend Futures

Dividend swaps emerged in the late 1990s to facilitate dividend trading and gained popularity with structured products.[6] Dividend futures, introduced around 2008, offer a listed alternative to dividend swaps. The popularity of dividend futures has risen since the Great Financial Crisis, as trading increasingly transitioned to centralized venues from the over-the-counter (OTC) market. Mixon and Onur (2016) explores the market for dividend swaps, using regulatory data, and discovered approximately 2 billion US dollars outstanding between dealers and end users (market-facing) and about another 4.4 billion between dealers (hedging). The Euro Stoxx 50 is the only market where listed futures clearly dominate, with approximately 10 times the notional of swaps outstanding in futures.[7]

I will explain the dynamics of dividend futures using a simple model, as presented by Willems (2019). To begin, consider a financial market that can be modeled with a filtered probability space $(\Omega, \mathcal{F}, \mathcal{F}_t, \mathbb{Q})$, where $\mathbb{Q}$ represents a risk-neutral pricing measure. Let X_t denote a polynomial jump-diffusion process, which models uncertainty and takes values in a state space $E \subseteq \mathbb{R}^d$, with dynamics given by:

[5] The specific markets are chosen for simple data availability reasons. The US SP 500 index is excluded from the sample for two reasons. The listed future was launched in 2015, providing a very short history; secondly, several contracts were missing, making it impossible to create a futures chain. A longer discussion on data employed in the paper is found in Section 9.6

[6] In this arrangement, the buyer agrees to pay a fixed dividend amount (fixed leg) at expiry, in exchange for the total qualifying dividends throughout the swap period (floating leg). Notably, the ex-date within the dividend swap period is irrelevant, as long as it falls within the swap period.

[7] The majority of dealer-to-dealer swaps are in the SP 500 market for dividends, while the Euro Stoxx 50 dealer hedging occurs almost exclusively on the listed futures, creating a much more active market for the listed futures examined.

$$dX_t = \kappa(\theta - X_t)dt + dM_t,$$

where $\kappa \in \mathbb{R}^{d\times d}$, $\theta \in \mathbb{R}^d$, and M_t is a d-dimensional martingale such that the generator $\mathcal{G}$ of X_t maps polynomials to polynomials of the same degree or lower.[8]

Let $n \in \mathbb{N}$, and denote by $\mathrm{Pol}_n(E)$ the space of polynomials on E with a degree of n or less. The dimension of $\mathrm{Pol}_n(E)$ is denoted by N_n. Let $h_1, \dots, h_{N_n}$ form a polynomial basis for $\mathrm{Pol}_n(E)$, and finally:

$$H_n(x) = (h_1(x), \dots, h_{N_n}(x))^T.$$

Given that $\mathcal{G}$ leaves $\mathrm{Pol}_n(E)$ invariant, there exists a unique matrix $G_n \in \mathbb{R}^{N_n\times N_n}$ representing the action of $\mathcal{G}$ on $\mathrm{Pol}_n(E)$ with respect to the basis $H_n(x)$. Without loss of generality, assume that $H_n(x)$ is the monomial basis.[9] From the invariance property of $\mathcal{G}$, one can derive the moment formula:

$$\mathbb{E}_t[H_n(H_T)] = \exp^{G_n(T-t)} H_n(X_t), \tag{1}$$

which is valid for all $T \geq t$. To define the price of the dividend forward, in this space, consider an index or equity that pays a continuous dividend stream at an instantaneous rate D_t, which varies stochastically. The cumulative dividend process is modeled as $C_t = C_0 + \int_0^t D_s ds$, where:

$$C_t = e^{\beta t} p^\top H_1(X_t). \tag{2}$$

Let C_t be a positive, non-decreasing, and absolutely continuous process with some parameters $\beta \in \mathbb{R}$ and $p \in \mathbb{R}^{d+1}$. This specification for C_t determines D_t, which is the instantaneous dividend rate implied by equation (2), given by:

$$D_t = e^{\beta t} p^\top (\beta I_d + G_1) H_1(X_t), \tag{3}$$

where I_d is the identity matrix.

Both the instantaneous dividend rate and the cumulative dividends load linearly on the factor process. The exponential scaling of C_t with parameter β ensures a non-negative instantaneous dividend rate. When all eigenvalues of κ have positive real parts, the parameter β controls the asymptotic risk-neutral expected growth rate of the dividends, which can be calculated using the moment formula (1):

[8]See, for example, Filipović and Larsson (2019), where the polynomial jump-diffusion process is a type of stochastic movement that incorporates both jumps and continuous diffusion components, with the added feature that the jump component exhibits a polynomial structure. This process is beneficial for modeling financial assets, as it allows for the inclusion of continuous and discontinuous price movements.

[9]A monomial basis is a set of monomials that can be combined linearly to form any polynomial in the given space. For example, in a two-dimensional space, a monomial basis could be $1, x, x^2$. This makes the problem easier to work with.

$$\lim_{T\to\infty} \frac{1}{T-t} \log\left(\frac{\mathbb{E}_t[D_T]}{D_t}\right) = \beta.$$

The time-t price of a continuously marked-to-market forward contract referencing the dividends to be paid over a future time interval $[T_1, T_2]$, where $t \leq T_1 \leq T_2$, is thus given by:

$$\begin{aligned} F_t^{(T_1,T_2)} &= \mathbb{E}_t\left[\int_{T_1}^{T_2} D_s ds\right] \\ &= \mathbb{E}_t\left[C_{T_2} - C_{T_1}\right] \\ &= p^\top \left(e^{\beta T_2} e^{G_1(T_2-t)} - e^{\beta T_1} e^{G_1(T_1-t)}\right) H_1(X_t), \end{aligned}$$

where I use the moment formula (1) in the last equality. Thus, the dividend forward price $F_t^{(T_1,T_2)}$ is an increasing function of β, and the risk-neutral expected growth rate of the dividends is the key factor that determines the price of the forward contract.[10]

2.1 Market Conventions

In the financial market, both dividend futures and dividend swaps are quoted in terms of amounts per index point. The computation for an index dividend future is akin to the index itself; however, the equity price is substituted with the dividend amount.[11] Consequently, the payout is the sum of all qualifying dividends, multiplied by the free float as determined by the index provider, of the stock disbursing that dividend, and divided by the divisor on the ex-date.

$$\text{Index Dividend} = \sum_{\text{All qualifying dividends}} \frac{\text{Number of shares of stock paying } D_i}{\text{Index divisor on ex-date of } D_i} D_i.$$

Index dividend futures and swaps are available with maturities of up to ten years, but the maturities available vary by market. It is important to note that extraordinary dividends are excluded from the qualifying dividends, but also that the proportion of special dividends as a fraction of total dividends has decreased over time, and is assumed to be negligible for the sample period under consideration, as discussed by DeAngelo et al. (2000).[12] Contracts are settled

[10]Henceforth referred to as $F_t^{(n)}$, where t is the trading day, and n is the period between T_2 when the contract matures. This is done since the paper features futures exclusively, thus t always equal T_1.

[11]Consider a stock index that is yielding 5 percent with certainty. The stock index is trading at 20 points, then the dividend future will be quoted at roughly 1 point.

[12]In summary, the payoff of a contract represents the total declared ordinary gross dividends on index constituents that transition to an ex-dividend status within a specified year.

in cash upon the expiration date, with no intermediate cashflows. For example, the payoff of the 2015 dividend futures contract on the Euro Stoxx 50 index consists of the declared ordinary gross dividends on index constituents that go ex-dividend between the third Friday of December 2014 and the third Friday of December 2015.

Utilizing dividend futures to interpolate the market's fluctuating dividend and GDP expectations is constrained by several factors at the shortest maturity and a few factors, including liquidity issues, at longer maturities.[13]

2.2 Building a Term Structure of Dividends

Since the futures data collected from the market is unstructured and lacks a clear term structure, it is necessary to construct one.[14] Rather than utilizing the most basic approach of working with nearby futures (nearbys), constant-maturity futures prices can be created by combining futures price data into a continuous time series.[15] I present two distinct methods for constructing dividend term structures, resulting in constant-maturity price series that represent a specific time-to-expiration remaining constant over time, providing an interpolated price for each time t. This technique is implemented using annual contracts with maturities ranging from 1 to 10 years in the future, depending on the market. Employing constant-maturity futures prices offers certain advantages, such as reducing some cyclical distortions observed in nearbys, but also presents some limitations.

First, it is essential to address challenges associated with this study, particularly the availability of prices for interpolation, especially in less active markets featuring irregularly shaped futures curves, which are prevalent in some of the opaque markets analyzed. Constant-maturity prices serve as an effective proxy for forward prices, assuming that an adequate number of futures maturities are traded for reasonable interpolation and no significant convexity bias exists.[16]

The convexity bias, as explored in the interest rate literature (e.g., Gupta

An extraordinary dividend, often referred to as a special or extra dividend, is typically a significantly larger amount that is announced with short notice, nonrecurring, and paid in cash. For instance, this type of dividend may occur when a company sells some assets and decides to return capital to shareholders.

[13]This is discussed thoroughly in Section 7.2. The US SP 500 index, for example, is excluded from the sample for two reasons. The listed future was launched in 2015, providing a very short history; secondly, several contracts were missing, making it impossible to create a futures chain.

[14]There are a plethora of methods for creating term structures for financial contracts, ranging from well-known techniques such as the Nelson-Siegel-Svensson exponential components framework (Svensson (1994)), a yield curve model that facilitates the calculation of forward rates and consists of three time-varying components, to more recent approaches that employ neural networks to determine term structures (see, for instance, Baruník and Malinská (2016)).

[15]It is believed that nearbys was employed by Gormsen and Koijen for their term structure.

[16]Some of the instruments studied are more popular in the OTC market (see e.g., Mixon and Onur (2016)), as the data provided by Refinitiv Eikon only covers the listed on exchange transactions that is a limitation to the study. A suggestion on how to improve the amount of quotes to solve this is available in Section 9.3

and Subrahmanyam (2000)), arises from discrepancies in the convexity of interest rate futures and forward rate agreement (FRA) instruments.[17] This bias can be ascribed to differences in margining practices, cash flows, and interest rate market volatility. Nonetheless, the convexity bias has diminished in recent years due to the transition of OTC swaps and FRAs to central counterparty clearing models and the influence of uncleared margin rules on OTC trading (see, for instance, Pozdnyakov and Steele (2009)). It is worth noting that in 2015, Mixon and Onur (2016) show, buy-side firms, which are typically the primary liquidity demanders in the dividend market transactions, were paying a marginal premium for OTC swaps compared to futures screen prices. In constructing the constant maturity futures pricing, this study assumes no convexity bias. While this is a strong assumption, implying no positive or negative relationship between dividends and interest rates, it is common practice with exchange-traded products.[18]

2.2.1 Nelson-Siegel Model

The first model I use to create the term structure is the Nelson-Siegel model (NS-model). Nelson and Siegel (1987) originally developed the model for a term structure of interest rates. It has been widely adopted for its simplicity, flexibility, and ability to capture various yield curve shapes with few parameters. The NS-model is a parsimonious model for fitting yield curves, typically represented by a continuous function of time to maturity. The model is given by the following equation:

$$y_t = \beta_0 + \beta_1 \frac{1 - e^{-\lambda_t n}}{\lambda_t n} + \beta_2 \left(\frac{1 - e^{-\lambda_t n}}{\lambda_t} - e^{-\lambda_t n} \right), \tag{4}$$

where $y(t)$ represents the yield at time to maturity t, β_0, β_1, and β_2 are the level, slope, and curvature parameters, respectively, and λ is the decay factor.

In order to modify the NS-model to accommodate dividend futures prices, it is crucial to be mindful of the distinctions between the two instruments. While interest rates embody the cost of borrowing funds over time, dividend futures represent contracts that enable investors to speculate on the dividends disbursed by an index or a collection of stocks over a predetermined duration. Consequently, the factors influencing the term structure of dividend futures prices differ from those affecting interest rates. Specifically, dividend futures prices rely on anticipations regarding future dividend disbursements, the growth rate of dividends, and market risk factors.

To model dividend futures prices using the NS framework, I can replace the yield $y(t)$ in Equation (4) with the dividend futures price $F_t^{(n)}$:

[17]The magnitude of the bias and the required adjustment in the interest rate market can be examined by calculating $Convexity\,Adjustment = Futures\,Implied\,Rate - FRA\,Rate$.

[18]With a positive (negative) relationship between dividend and interest rates, the dividend forward price would be smaller (larger) than the dividend futures price.

$$F_t^{(n)} = \beta_0 + \beta_1 \frac{1 - e^{-\lambda_t n}}{\lambda_t n} + \beta_2 \left(\frac{1 - e^{-\lambda_t n}}{\lambda_t n} - e^{-\lambda_t n} \right), \tag{5}$$

where $F_t^{(n)}$ represents the dividend futures price at time to maturity t. The parameters β_0, β_1, and β_2 can be interpreted in a similar manner as in the original NS-model but now reflect the long-term level, slope, and curvature of the dividend futures term structure, respectively.

While the NS-model can be adapted to model dividend futures prices, it is important to recognize the potential implications of this approach: Firstly, the parameters β_0, β_1, and β_2 in the context of dividend futures may have different economic interpretations than in the case of interest rates. For example, the long-term level parameter, β_0, can be interpreted as the long-term dividend growth rate, while the slope and curvature parameters, β_1 and β_2, might capture the market's expectations of changes in dividend growth rates and risk factors over time. These variables are also highly influenced by the market's different idiosyncrasies discussed thoroughly in Section 7.2.

Secondly, the NS-model assumes a three-factor structure, which might not capture all the factors influencing dividend futures prices. More advanced models, such as multi-factor or dynamic models, may be better suited to capture the complex relationships between dividend futures prices, dividend growth rates, and market risk factors. As I am not focusing on researching the dividend term structure models I have opted for this simpler approach.[19] Furthermore, like the original NS-model for interest rates, the adapted model for dividend futures prices will not be arbitrage-free, as shown by Filipović (1999).[20]

2.2.2 Cubic Spline Model

The second type of term structure I create utilizes a cubic spline as described by Green and Silverman (1993), adjusted for futures. The goal of the method is to use a cubic spline to interpolate a set of futures prices with varying maturities. The function is minimized by choosing the coefficients of the spline function to minimize the sum of squared second derivatives of the function, subject to a smoothing constraint.

Suppose a set of dividend futures prices $F_t^{(1)}, F_t^{(2)}, \ldots, F_t^{(t_n)}$ for maturities $t_1 < t_2 < \cdots < t_n$. I want to create a continuous function F_t that passes through these futures prices and can be used to value futures contracts with any maturity between t_1 and t_n.

[19] Given that the NS-model was not specifically designed for dividend futures prices, it would be crucial to validate its performance using out-of-sample testing or cross-validation. I do conduct comparisons in the estimates produced by the Spline-model and the NS-model and find minor differences. For a comprehensive paper on dividend term structures see, for example, Kragt et al. (2020).

[20] This limitation is particularly relevant for pricing complex financial derivatives or risk management applications, where an arbitrage-free model is essential, but is less of a problem in this context.

To achieve this, I can use the cubic smoothing spline function, which has the following form:

$$F_t = \sum_{i=1}^{n} c_i S_{i,t},$$

where c_i are the coefficients that determine the shape of the spline, and $S_{i,t}$ are cubic B-spline basis functions.

The cubic B-spline basis functions are piecewise cubic polynomials that are defined on subintervals of $[t_1, t_n]$, and they have the following recursive definition:

$$S_{i,k}(t) = \frac{t - t_i}{t_{i+k-1} - t_i} S_{i,k-1}(t) + \frac{t_{i+k} - t}{t_{i+k} - t_{i+1}} S_{i+1,k-1}(t).$$

The k-th order B-spline basis functions are defined recursively in terms of the $(k-1)$-th order B-spline basis functions, with the base case being the 0-th order B-spline basis functions, which are defined as follows:

$$S_{i,0}(t) = \begin{cases} 1, & \text{if } t_i \leq t < t_{i+1} \\ 0, & \text{otherwise.} \end{cases}$$

The coefficients c_i are chosen to minimize the sum of squared second derivatives of the function F_t, subject to a smoothing constraint. Specifically, I minimize the following function:

$$\sum_{i=1}^{n-2} \left(\frac{d^2 F_{t_i}}{dt^2} \right)^2 + \lambda \int_{t_1}^{t_n} \left(\frac{d^2 F_t}{dt^2} \right)^2 dt,$$

where λ is a smoothing parameter that determines the amount of smoothing applied to the function.

Once the coefficients c_i have been determined, the function F_t can be used to value contracts with any maturity between t_1 and t_n, by simply evaluating F_t at the desired maturity. In this way, the method allows us to create a continuous dividend futures curve from a set of futures prices with varying maturities.

The correlation between the term structures of the Nikkei 225 and Euro Stoxx 50 indices exhibit distinct differences across the various samples studied as shown in Table 1. While some maturities show strong correlations, others demonstrate a weaker relationship between the term structures. However, despite these disparities, the overall estimates of the term structure correlations are still broadly similar.[21] This similarity suggests that, although the specific market conditions in each region may affect the individual term structures, the general trends and patterns observed in the term structures are consistent across both models, furthermore they also produce roughly the same estimates as shown later. Corresponding tables for other markets studied can be found in Appendix 10.2.

[21] The discrepancy seems to be driven by differences in variance across the curve for different samples, however more research is needed into the topic.

Table 1: Correlation Between Term Structures

(a) Nikkei 225

	CS 1	CS 2	CS 3	CS 4	CS 5	CS 6	CS 7	CS 8	CS 9	CS 10
NS 1	1.00	0.98	0.96	0.94	0.92	0.91	0.90	0.90	0.90	0.90
NS 2	0.99	0.99	0.98	0.97	0.96	0.95	0.94	0.94	0.93	0.93
NS 3	0.97	0.99	0.99	0.98	0.97	0.96	0.96	0.95	0.95	0.95
NS 4	0.96	0.99	0.99	0.98	0.98	0.97	0.97	0.96	0.96	0.96
NS 5	0.96	0.99	0.99	0.99	0.98	0.98	0.97	0.97	0.97	0.96
NS 6	0.95	0.98	0.99	0.99	0.98	0.98	0.98	0.97	0.97	0.97
NS 7	0.94	0.98	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.97
NS 8	0.94	0.98	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.98
NS 9	0.94	0.98	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.98
NS 10	0.93	0.97	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.98

(b) Euro Stoxx 50

	CS 1	CS 2	CS 3	CS 4	CS 5	CS 6	CS 7	CS 8	CS 9	CS 10
NS 1	0.99	0.63	0.50	0.35	0.29	0.29	0.30	0.22	0.21	0.20
NS 2	0.83	0.86	0.74	0.66	0.60	0.58	0.57	0.44	0.40	0.36
NS 3	0.68	0.88	0.78	0.76	0.71	0.69	0.67	0.58	0.53	0.48
NS 4	0.59	0.86	0.77	0.79	0.76	0.75	0.73	0.67	0.63	0.58
NS 5	0.52	0.83	0.75	0.79	0.78	0.78	0.77	0.73	0.70	0.66
NS 6	0.47	0.79	0.73	0.78	0.79	0.79	0.79	0.77	0.75	0.71
NS 7	0.44	0.74	0.69	0.74	0.77	0.79	0.80	0.80	0.78	0.76
NS 8	0.42	0.68	0.65	0.70	0.75	0.78	0.80	0.80	0.80	0.79
NS 9	0.40	0.63	0.61	0.66	0.72	0.76	0.79	0.80	0.81	0.80
NS 10	0.38	0.57	0.57	0.60	0.68	0.73	0.77	0.78	0.80	0.81

Note: This table displays the correlation coefficients for the term structures of the Nikkei 225 and Euro Stoxx 50 indices. The data is generated from historical market data, with each cell representing the correlation between the respective term structures in the two indices. Higher values (closer to 1) indicate stronger positive correlations, while lower values (closer to 0) indicate weaker correlations. The table provides a comparative overview of the term structure relationships between the two major indices.

3 Changing dividend growth expectations

The lower bound on dividend growth expectations is derived from futures prices, employing the method utilized in Gormsen and Koijen (2020). The relationship between equity prices and dividend futures is first emphasized. The price of a stock at time t can be represented as:

$$S_t = \sum_{n=1}^{\infty} \frac{\mathbb{E}_t[D_{t+n}]}{1 + \mu_t^{(n)}}$$

where D_{t+n} denotes the expected dividend paid out in n years' time, and $\mu_t^{(n)}$ signifies the cumulative discount rate associated with the cash flow. Although the price of a stock does not allow for the observation of a specific dividend's present value, the no-arbitrage assumption implies that the instantaneous dividend rate, or rather hypothetical spot price, $P_t^{(n)}$ of an n-year dividend futures contract would provide this information:

$$P_t^{(n)} = \frac{\mathbb{E}_t[D_{t+n}]}{1 + \mu_t^{(n)}}. \tag{6}$$

This hypothetical spot price is however unobservable, but the future, which is a observable, can be expressed as:

$$F_t^{(n)} = \frac{\mathbb{E}_t[D_{t+n}]}{1 + \theta_t^{(n)}} \tag{7}$$

where $\theta_t^{(n)}$ represents the n-period expected excess return on the risk associated with the n-period dividend. The hypothetical spot price and futures price are connected through the no-arbitrage condition $F_t^{(n)} = (1 + y_t^{(n)})P_t^{(n)}$, in which $y_t^{(n)}$ denotes the risk-free rate. Thus, for the no-arbitrage condition to be upheld, the sum of an infinite number of (hypothetical) dividend futures discounted by the risk-free rate ($y_t^{(n)}$) must equal the stock price:

$$S_t = \sum_{n=1}^{\infty} \frac{F_t^{(n)}}{1 + y_t^{(n)}}$$

as $(1 + \theta_t^{(n)})(1 + y_t^{(n)}) = 1 + \mu_t^{(n)}$. The interrelation between dividend futures prices and stock prices creates the opportunity to decompose the market's expectation of dividend growth by maturity. With straightforward assumptions, a lower bound growth expectation for dividends can be derived using dividend futures prices. The dividend futures price must be priced by the n-period stochastic discount factor (SDF), m_{t+n}, as:[22]

$$F_t^{(n)} = \frac{\mathbb{E}_t[m_{t+n} D_{t+n}]}{\mathbb{E}_t[m_{t+n}]}.$$

By dividing the equation by the dividend at time t and defining dividend growth as $G_t^{(n)} = \frac{D_{t+n}}{D_t}$, the following expression is obtained:

$$\frac{F_t^{(n)}}{D_t} = \frac{\mathbb{E}_t[m_{t+n} G_t^{(n)}]}{\mathbb{E}_t[m_{t+n}]}.$$

Utilizing the property $E[X \cdot Y] = E[X] \cdot E[Y] + Cov[X, Y]$, the expression can be rewritten as:

$$\begin{aligned} \frac{F_t^{(n)}}{D_t} &= G_t^{(n)} + \frac{Cov[m_{t+n}, G_t^{(n)}]}{\mathbb{E}_t[m_{t+n}]} \\ &= \frac{G_t^{(n)}}{\Theta_t^{(n)}} \end{aligned}$$

where

$$\Theta_t^{(n)} = \left(1 + \frac{Cov[m_{t+n}, G_t^{(n)}]}{\mathbb{E}_t[m_{t+n}] G_t^{(n)}} \right)^{-1}$$

represents the gross risk premium associated with dividend growth. By examining the change in expected dividend growth over a short time horizon from t to t', one can assume $D_t \approx D_{t'}$,

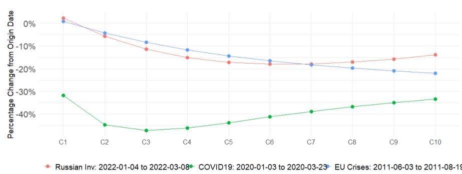
$$\Delta F_{t'}^{(n)} = \frac{F_{t'}^{(n)}}{F_t^{(n)}} = \frac{G_{t'}^{(n)}}{G_t^{(n)}} \frac{\Theta_t^{(n)}}{\Theta_{t'}^{(n)}} = \frac{\Theta_t^{(n)}}{\Theta_{t'}^{(n)}} \Delta G_{t'}^{(n)}.$$

[22]The SDF is thoroughly explained and derived in its simplest form in the Appendix 9.4.

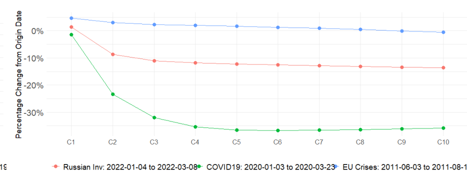
Assuming risk aversion does not decrease between time t and t', implying that $\Theta_{t'}^{(n)} \geq \Theta_t^{(n)}$.[23] This assumption is reasonable when modeling investors' response to a sudden GDP shock, such as the outbreak of a war, a global pandemic, or a financial crisis.[24] Consequently, a lower bound on dividend growth expectations can be derived:

$$E[\Delta G_{t'}^{(n)}] - 1 \geq \Delta F_{t'}^{(n)} - 1.$$

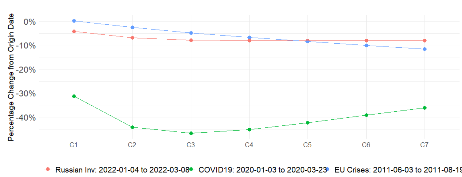
Figure 1: Comparing Percentage Change of the Lower Bound across Three Major Events



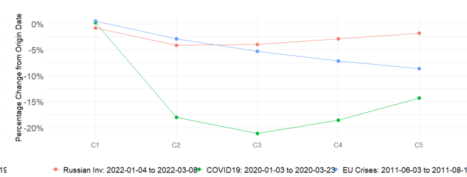
(a) Euro Stoxx 50.



(b) Nikkei 225.



(c) FTSE 100.



(d) SMI 30.

Note: The figures presents the percentage change in lower bound dividend expectations, calculated from the beginning of the year (January 1st) to the specified dates in the legend. However, for the Eurocrises, the GDP shock is defined from June onwards due to data availability. The selected date corresponds to a critical period in the Eurocrises, marked by events such as Portugal's impending default, the approval of the second rescue package for Greece, and the introduction of new European austerity measures.

Figure 1 investigates the lower-bound dividend growth expectations during three critical events: the 2022 Russian invasion of Ukraine, the 2020 onset of the global pandemic, and the 2011 Euro crisis.[25] Distinct yet varying effects are observed across different time periods for the markets. One intriguing change in expectations is evident in Switzerland's (SMI 30 10d) V-shaped curve, a recurring pattern for this market.[26] The Euro area's (Euro Stoxx 50) post-pandemic

[23] A more formal expression of this assumption would be: if risk aversion increases as $t < t'$, this implies $\Theta_{t'}^{(1)} \geq \Theta_t^{(1)}$.

[24] Despite the presence of notable tensions preceding the invasion of Ukraine, it is probable that the majority of investors held a viewpoint akin to that of foreign policy scholars, which deemed the likelihood of Russia's invasion of Ukraine as low. A similar sentiment could be applied to the occurrence of the pandemic and financial crises. Nonetheless, it can be inferred from the market's response that none of these events were anticipated, and consequently, had unforeseen, detrimental effects on the economy.

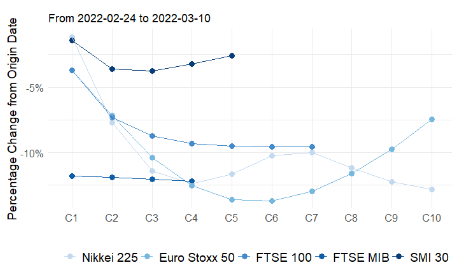
[25] The remaining graphs can be found in Appendix 10.3.

[26] This may be due to the issuance of structured products as discussed in 7.2, but further research is needed on this topic.

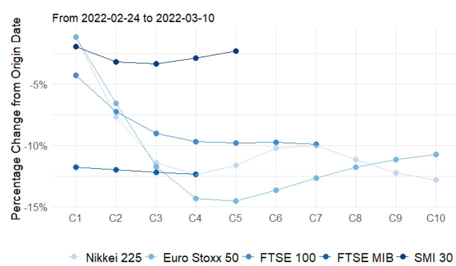
and post-invasion decreases are similar in curvature but differ in magnitude, with expectations declining by approximately 10 and 50 percent, respectively, for medium-term dividends. In contrast, the impact on long-term dividends is less pronounced, possibly reflecting investors' perceptions of long-term supply chain and energy demand effects. A more detailed view of the changing expectations can be found in Table 11.

The United Kingdom (FTSE 100) experienced a smaller decrease during the Russian invasion than during the COVID-19 pandemic in medium-term expectations, while long-term expectations remained relatively stable. Figure 1 underscores the relationships between the Euro crisis, the coronavirus pandemic, and the invasion, revealing a stark contrast between lower-bound expectations of dividend growth post-invasion compared to the impacts of the Euro crisis or the coronavirus pandemic. The Russian invasion of Ukraine has led to downward revisions in dividend expectations, particularly for the Euro area and the United Kingdom, ranging from 5 to 10 percent.

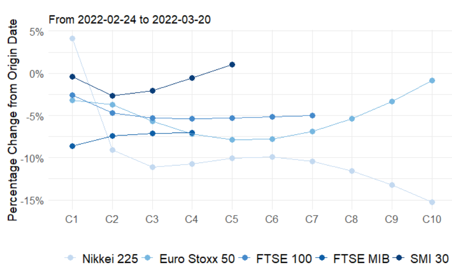
Figure 2: Lower Bound Change in Expected Dividend Growth After Russian Invasion of Ukraine.



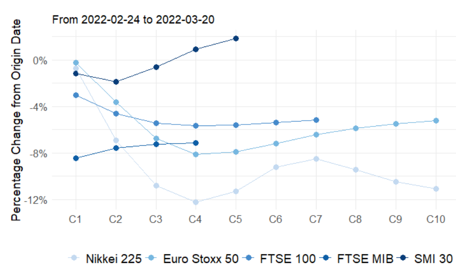
(a) NS-Model. 2022-03-10.



(b) Cubic Spline. 2022-03-10.



(c) NS-Model. 2022-03-20.



(d) Cubic Spline. 2022-03-20.

Note: This figure depict the lower bound change in expected growth over the next n years, $\mathbf{E}_t[\Delta G_{t'}^{(n)}] - 1$. The start date of the comparison is the start of the Russian invasion of Ukraine. The effects are smaller than those measured during for example the COVID-19 pandemic. The corresponding GDP estimates for European counteris is found in Figure 14.

Figure 2 provides a detailed analysis of the lower bound's effects during the invasion using both term structure models. While minor discrepancies exist between the two models, the most significant differences stem from the markets

Table 2: Detailed Showcase of Changes In the NS-Models

	2022-03-10						2022-03-20				
Contract	Nikkei 225	Euro Stoxx 50	FTSE 100	FTSE MIB	SMI 30	Contract	Nikkei 225	Euro Stoxx 50	FTSE 100	FTSE MIB	SMI 30
C1	-0.012	-0.037	-0.037	-0.118	-0.014	C1	0.041	-0.032	-0.026	-0.086	-0.004
C2	-0.077	-0.072	-0.073	-0.119	-0.036	C2	-0.091	-0.037	-0.047	-0.074	-0.027
C3	-0.114	-0.104	-0.087	-0.120	-0.038	C3	-0.111	-0.056	-0.053	-0.071	-0.020
C4	-0.124	-0.125	-0.093	-0.122	-0.032	C4	-0.107	-0.072	-0.054	-0.071	-0.005
C5	-0.116	-0.136	-0.095		-0.026	C5	-0.100	-0.079	-0.053		0.011
C6	-0.102	-0.137	-0.096			C6	-0.099	-0.078	-0.052		
C7	-0.100	-0.130	-0.096			C7	-0.104	-0.069	-0.050		
C8	-0.112	-0.116				C8	-0.116	-0.054			
C9	-0.122	-0.098				C9	-0.132	-0.033			
C10	-0.128	-0.075				C10	-0.152	-0.008			

Note: This table displays the percentage point change in lower-bound dividend growth expectations subsequent to Russia's invasion of Ukraine, expressed as decimals (e.g., 0.026 represents a 2.6% change). The dates presented at the top of the table indicate a cutoff from the reference date of February 24th. The corresponding figure featuring the Cubic Spline-model is found in Table 10.

studied. Approximately two weeks into the invasion, substantial divergences between European nations are observed in both the short-end and long-end of expectations. Post-invasion expectations exhibit a downward trend, potentially due to limited transactions and a perceived lesser impact on the short end.[27] The expectations of Italy (FTSE MIB) and the Euro area (Euro Stoxx 50) were most adversely affected at the invasion's onset (detailed figures in Table 2). In contrast, the United Kingdom (FTSE 100) and especially Switzerland (SMI 30) showed greater resilience.

Potential explanations for this disparity following Ukraine's invasion may be linked to factors such as Italian bank exposures, which represented over $25 billion at the end of September, according to Bank of International Settlements data, and reliance on Russian oil imports, which could contribute to the observed variation in market reactions.

4 Expected dividend growth

The method developed by Van Binsbergen et al. (2013) is applied to extrapolate the expected dividend growth from dividend futures. The authors demonstrate that dividend futures prices can be used to construct equity yields, which are analogous to bond yields. To derive the equity yield, the derivation is briefly covered before employing dividend futures to calculate the anticipated dividend growth.

The expected annual growth rate of dividends $G_{t,n}$ between time t and $t+n$ is defined as follows:

$$G_{t,n} = \mathbb{E}_t \left[\left(\frac{D_{t+n}}{D_t} \right)^{\frac{1}{n}} \right],$$

[27] As discussed in the section addressing the asynchronous nature of dividend futures and the invasion's timing, the short end could be more firmly anchored due to the near certainty of well-known payouts by this date.

where D_t denotes the dividend at time t. This expression can be rearranged to:

$$D_t G_{t,n}^n = \mathbb{E}_t \left[D_{t+n} \right].$$

Subsequently, the expected present value of the future dividend - i.e., the spot price, or instantaneous forward, of the dividend future, $P_{t,n} = \frac{\mathbb{E}_t[D_{t+n}]}{M_{t+n}^n}$, where M_{t+n}^n is the discount rate — can be written as:

$$P_{t,n} = D_t \left(\frac{G_{t,n}}{M_{t,n}} \right)^n .$$

This expression can be further simplified to:

$$P_{t,n} = D_t \exp(n(g_{t,n} - \mu_{t,n})),$$

where $g_{t,n} = \ln(G_{t,n})$ and $\mu_{t,n} = \ln(M_{t,n})$. In this case, the discount rate is divided into two components: the nominal bond yield $y_{t,n}$ and the risk premium $\theta_{t,n}$, which investors require as compensation for assuming dividend risk. Consequently, I obtain:

$$P_{t,n} = D_t \exp(n(g_{t,n} - y_{t,n} - \theta_{t,n})).$$

Finally, I define the equity yield as:

$$e_{t,n} = \frac{1}{n} \ln \left(\frac{D_t}{P_{t,n}} \right) = y_{t,n} + \theta_{t,n} - g_{t,n}.$$

Utilizing dividend futures and the method established by Van Binsbergen et al. (2013), I can derive expected dividend growth and characterize the equity yield as a function of the nominal bond yield and the equity risk premium.[28]

To estimate expected dividend growth, I utilize equity yields constructed based on the dividend futures price $F_t^{(n)} = P_{t,n} \exp(n y_{t,n})$, where $y_{t,n}$ is the nominal bond yield and $\theta_{t,n}$ is the risk premium demanded by investors for assuming dividend risk. I approximate the equity yields as:

$$\hat{e}_t^{(n)} = \frac{1}{n} \ln \left(\frac{D_t}{F_t^{(n)}} \right),$$

where D_t is the underlying dividend index or the approximate index for cumulative dividends, as described in the Appendix 9.1.

[28] In this context, the equity risk premium resembles a dividend risk premium, representing the additional return over the nominal "risk-free" bond yield, at that specific maturity, that an investor demands to hold the dividend derivative.

Van Binsbergen et al. (2013) demonstrate that equity yields possess valuable predictive characteristics for extrapolating expected dividend growth[29]. To harness these characteristics, I use a technique similar to Gormsen and Koijen (2020). I analyze the impact of different GDP shocks on expected dividend growth, however, limitations in data availability prevent me from uniformly matching the appropriate current cumulative dividend D_t with the dividend futures price $F_t^{(n)}$ across all markets. Therefore, I use the underlying dividend index for some markets, with modifications to capture the sum of the last year's dividends, while an approximate index for cumulative dividends is created for other markets, similar to that of Van Binsbergen et al. (2013).[30]

I present the setup of regression model, to derive $\beta_{1,i}^D$ as follows:

$$\Delta D_{i,t} = \beta_{0,i}^D + \beta_{1,i}^D \hat{e}_{i,t}^{(n)} + \epsilon_{i,t+1}$$

Here, $\Delta D_{i,t} = \frac{D_{t+1}}{D_t}$ represents the dividend growth between times t and $t+1$. The regression shows how changes in forward equity yields are connected to dividend growth. In essence, forward equity yields are required to either forecast dividend growth rates or the excess returns on dividend-paying assets, or a combination of both. A high value of the forward equity yield indicates that either risk premium is high or that the expected dividend growth rate is low. As a result, forward equity yields serve as suitable predictors for dividend growth across various maturities.[31]

Contrary to the quarterly data collection approach employed by Gormsen and Koijen (2020), the observations in this analysis are gathered on a daily basis, with i denoting the specific market studied. The primary objective is to estimate the beta parameters that calibrate the forward-looking estimates by conducting a regression analysis of the newly formulated variable onto the actual dividend growth. At the beginning of the year, the anticipated dividend growth is estimated through this regression. Table 3 presents the computed values for β_1^D.[32]

The strength of these relationships is not uniform across countries; Japan exhibits the most pronounced negative association, while Germany demonstrates the weakest. Subsequently, the beta parameters are employed to adjust the forward-looking estimates. Lastly, the expected dividend growth from the commencement of the year is determined using regression analysis.[33]

[29] This is evident in the aforementioned formula, where equity yields must contain information about either expected excess returns, expected dividend growth, or both

[30] A detailed description is found in the Appendix 9.1. Specifically, the underlying dividend indexes were not readily accessible for all markets. Therefore, an approximate index for cumulative dividends was created, utilizing the methods outlined in Van Binsbergen et al. (2013). In contrast, the underlying dividend index was used for the remaining markets, with modifications to capture the sum of the last year's dividends.

[31] By excess returns in this context I mean returns above those of bonds.

[32] A pooled regression is also conducted to increase the sample size. However, the need to do it drastically diminishes when using daily data instead of quarterly as in Gormsen and Koijen (2020) it also seems to produce spurious results. The table can be found in the Appendix.

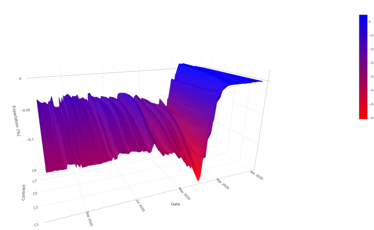
[33] Germany's results are highly unreliable due to the low number of actual transactions

Table 3: Summary of Regression Coefficients for each Country and Term Structure

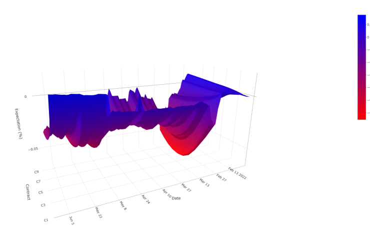
Country and Model	**Coefficient**									
	$\beta^D_{1,1}$	$\beta^D_{1,2}$	$\beta^D_{1,3}$	$\beta^D_{1,4}$	$\beta^D_{1,5}$	$\beta^D_{1,6}$	$\beta^D_{1,7}$	$\beta^D_{1,8}$	$\beta^D_{1,9}$	$\beta^D_{1,10}$
EuroZone	-0.31	-0.31	-0.31	-0.30	-0.30	-0.30	-0.30	-0.30	-0.30	-0.30
EuroZone_NS	-0.31	-0.31	-0.31	-0.30	-0.30	-0.30	-0.30	-0.30	-0.30	-0.30
Japan	-0.60	-0.58	-0.57	-0.56	-0.54	-0.53	-0.52	-0.51	-0.50	-0.50
Japan_NS	-0.60	-0.58	-0.57	-0.56	-0.54	-0.53	-0.52	-0.51	-0.50	-0.50
UnitedKingdom	-0.45	-0.45	-0.45	-0.45	-0.45	-0.44	-0.44			
UnitedKingdom_NS	-0.45	-0.45	-0.45	-0.45	-0.45	-0.44	-0.44			
France	-0.40	-0.40	-0.40	-0.40	-0.40					
France_NS	-0.40	-0.40	-0.40	-0.40	-0.40					
Switzerland	-0.48	-0.48	-0.48	-0.48	-0.48					
Switzerland_NS	-0.48	-0.48	-0.48	-0.48	-0.48					
Germany	-0.38	-0.38	-0.38	-0.38	-0.38					
Germany_NS	-0.38	-0.38	-0.38	-0.38	-0.38					

Note: The estimated coefficients ($\beta^D_{1,i}$) for various countries and models, highlighting the relationship between the dependent variable of spot dividends and the forward equity yeilds. The coefficients are presented for different models, the coefficients with a NS-model sample ar indicated by "_NS"). In general, the table demonstrates a consistent negative relationship between the dependent and the independent variables across all countries and models.

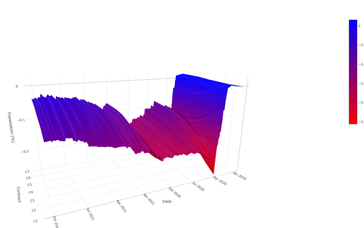
Figure 3: Development of dividend growth expectations.



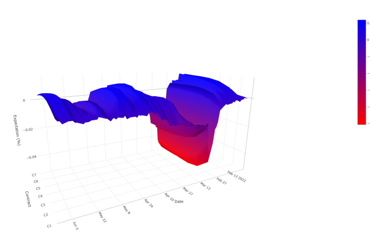
(a) Euro Stoxx 50 2020.



(b) Euro Stoxx 50 2022.



(c) FTSE 100 2020.



(d) FTSE 100 2022.

Note: The 3D surface plot presented represents the adjusted expectations of GDP for various contracts over time. The expectations have been adjusted based on a series of error terms and coefficients, which are calculated for each contract. The data is organized by contract names on the x-axis, dates on the y-axis, and expectations on the z-axis, allowing for a comprehensive view of the relationship between these factors. The surface plot demonstrates the dynamics of contract expectations and how they change over time, highlighting potential trends or patterns. Additionally, the adjusted expectations are multiplied by country-specific coefficients, providing insights into the unique characteristics of the specified country's contract expectations. This visualization allows users to gain a deeper understanding of the contract expectations' behavior and their association with time and other contracts.

contained in the data sample from Refinitiv Eikon. Nevertheless, these unreliable results point to a print in line with that of the Euro Stoxx 50.

Figure 3 depicts the investors' forward-looking dividend growth expectations across the term structure.[34] In light of the recent invasion news, these expectations have experienced a substantial decline. Panels 3b and 3d reveal that the market anticipated an increase prior to the 2022 invasion, which subsequently dropped below zero. Following the invasion, the most pronounced decline in expectations occurred in the midterm, resulting in a hump-shaped pattern on the surface. Both the short-term and long-term expectations exhibited the least reaction, as evidenced in panels 3b and 3d. During 2020, the market response was more pronounced in the short end, with expectations decreasing before gradually recovering over time.

Detailed results for several time periods are provided in the Appendix. The findings for the COVID-19 pandemic are consistent with those of Gormsen and Koijen (2020), particularly for the markets we both examine. Point estimates for the Euro Stoxx 50 and Nikkei, during the onset of the COVID-19 pandemic, are comparable, with my estimates being somewhat lower.[35] Interestingly, there appears to be some convergence across the studied markets, with Italy, which was hardest hit during the initial phases of the pandemic, also experiencing the most significant downward revision of growth expectations.

For the Eurocrisis and the specific date chosen to symbolize its onset, I also observe a sharp disparity between the different samples studied. Italy, which was severely impacted by the ongoing turmoil and received a bailout during the period, exhibited the most significant market reaction.[36] In contrast, Japan experienced a more muted response to the ongoing turbulence but faced market jitters at an earlier stage. This variation in market reactions highlights the importance of considering the specific contexts and economic conditions of each market when analyzing the effects of global crises on growth expectations.

5 Estimating Lower Bound Implied GDP Growth

This section outlines the methodology employed to estimate the lower bound of implied GDP growth expectations, drawing upon the approach proposed by Gormsen and Koijen (2020). Given that dividends represent claims to the surpluses generated by firms operating in the real economy, it is reasonable to anticipate a relationship between the dividends of listed companies and GDP. By extending the historical relationship between real dividends and real GDP, I can leverage parameters obtained from regression analysis to estimate the

[34]In Figure 6, the expectation change "across the curve" signifies that contingent upon the number of available contracts, the expectations alter "n" years into the future.

[35]In Table 13 denoted as EU and JAP.

[36]During the Eurocrisis, Italy encountered several significant events that contributed to the observed disparity in growth expectations. In the summer, when point estimates were taken, Italy grappled with the crisis's effects, leading to the implementation of austerity measures. In September 2011, the Italian Parliament approved a €54 billion austerity package, pledging to balance the budget by 2013. This package aimed to address Italy's growing debt burden and restore investor confidence. Another critical event transpired during the summer when Prime Minister Silvio Berlusconi faced mounting pressure, ultimately resigning in November 2011 amid doubts about Italy's ability to manage its debt.

lower bound of implied GDP growth expectations. It is vital to recognize that these are *implied* expectations, derived from the relationship between dividends and GDP, and not necessarily actual GDP growth expectations.[37] It is crucial to emphasize that GDP series encompass numerous components unrelated to dividends; therefore, only a portion of this variation is captured.

5.1 The relationship between GDP and dividends

To extract the business cycle component for both the dividend and GDP series, a Hamilton-filter is employed.

The Hamilton filter is favored over the more widely-known Hodrick-Prescott filter (HP-filter), popularised by Hodrick and Prescott (1997), for several reasons. First, Hamilton (2018) demonstrates that the series produced by the HP-filter may exhibit spurious dynamic relations that are not supported by the underlying data-generating process. In other words, the HP-filter might introduce artificial patterns into the data that are not present in the original series. Second, the filtered values at the end of the sample can significantly differ from those in the middle, which means that the HP-filter may produce inconsistent results throughout the series. These end-of-sample values are also subject to spurious dynamics that may lead to misleading interpretations. Finally, when conducting a statistical formalization of the problem, the resulting values for the smoothing parameter in the HP-filter may deviate from common practice. For example, the value for the parameter lambda may become smaller than what is typically considered appropriate, leading to an over-smoothed series. The Hamilton-filter tries to solve these issues.

Applying the Hamilton-filter in this context involves running a regression where z_t represents the logarithm of either real dividends or real GDP, given by:

$$z_t = d_0 + \sum_{j=8}^{11} d_i z_{t-j} + c_t.$$

Here, I obtain the residual c_t, which serves as the cyclical component for either series.[38]

As previously pointed out, there is ample evidence supporting the correlation between GDP and dividends. For instance, Ragnvid (2006) shows that economic activity and dividend trends exhibit a close relationship over extended time periods and that dividends display a mean-reverting tendency towards GDP. Similarly, Rozeff (1984) asserts that the evolution of dividends over time is

[37]In other words, the question being addressed is: "What will be the GDP growth assuming investors' expectations of dividends are accurate, and the historical relationship between dividends and GDP remains valid?"

[38]The frequency of the GDP data is quarterly, as that is the most common publication time window across various national databases.

highly correlated with GDP growth.[39]

As illustrated in Figure 4, the cyclical components of GDP and dividends demonstrate a strong relationship graphically. This is further reinforced by the two series exhibiting a substantial correlation across all samples used in this study. Moreover, a Johansen-Procedure, introduced by Johansen (1991), is employed to demonstrate that the cyclical components of GDP and dividends are related through a cointegration test, indicating that the two series are closely linked.

The Johansen test is a statistical procedure used to assess cointegration of several time series, typically integrated of order one, denoted as $I(1)$, with k lags. Cointegration would imply a long-term equilibrium relationship between dividends and GDP. This test is particularly useful in analyzing multiple time series that share a common trend, even though their individual paths might diverge in the short term.

In its general form, the Johansen test starts with a Vector Autoregression model, which can be specified as:

$$\mathbf{X}t = \Pi_1 \mathbf{X}t - 1 + \cdots + \Pi_k \mathbf{X}_{t-k} + \mu + \Phi D_t + \epsilon_t,$$

where, $\mathbf{X}t$ is the vector of the time series under analysis, and Π_i are the coefficient matrices corresponding to the k lags. Φ is a matrix of coefficients for any deterministic terms D_t, ϵ_t is the error term, and μ is a constant term.

The corresponding specification for the Vector Error Correction Model is given by:

$$\Delta \mathbf{X}t = \Gamma_1 \Delta \mathbf{X}t - 1 + \cdots + \Gamma_{k-1} \Delta \mathbf{X}t - k + 1 + \Pi \mathbf{X}t - k + \mu + \Phi D_t + \epsilon_t$$

In this representation, $\Delta \mathbf{X}t$ denotes the first differences of the time series, Γ_i are the coefficients that capture the short-run, and Π is a matrix that reflects the long-run relationship among the dividends and GDP. Specifically, $\Gamma_i = -(I - \Pi_1 - \cdots - \Pi_i)$, for $i = 1, \ldots, k-1$, and $\Pi = -(I - \Pi_1 - \cdots - \Pi_k)$.

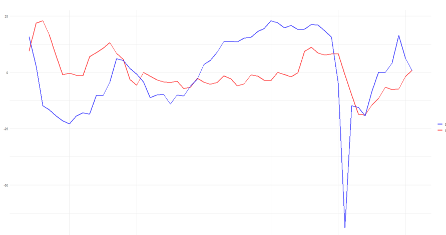
The Johansen test focuses on the rank of the Π matrix, which determines the number of cointegrating relationships among the series. The presence of cointegration implies that the variables share a common stochastic trend, allowing for a long-run equilibrium relationship to be estimated.

The cointegration relationships between the cyclical components of GDP and dividends for various countries are presented in Table (16). The results suggest that France, the United Kingdom, Japan, United States, Italy and Switzerland have cointegrated cyclical dividends and GDP series. Eigenvalues indicate the proportion of the variance of the two series explained by each cointegration vector, with higher eigenvalues signifying a stronger cointegration relationship. The results reveal that France and Japan have the highest eigenvalues, at 0.44 and 0.31, respectively, suggesting a stronger relationship between the two series.

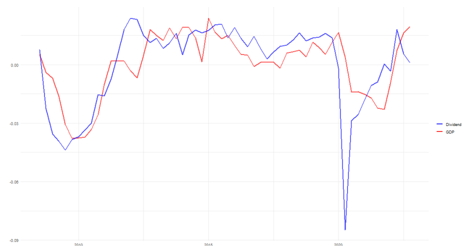
[39] Gormsen and Koijen (2020) find a time series correlation of 54%, but they also note that the two series seem to have an asymmetric relation, with leverage effects to the downside.

Test statistics provide insight into the strength of the cointegration relationship and the significance of the test. A higher test statistic implies stronger evidence of cointegration, with a value exceeding the 5% critical value indicative of a statistically significant result. The findings demonstrate that France, Japan, the United Kingdom, and the United States possess a robust and significant cointegration relationship between the two series, while Switzerland and Italy exhibit a weaker and less significant relationship. The weights of the cyclical components of the GDP and dividend series reveal the influence of each series on the cointegration vector. The outcomes indicate that the cyclical component of the GDP series has a more substantial impact on the cointegration relationship in all countries, except for Japan, where the dividend series has a higher weight.

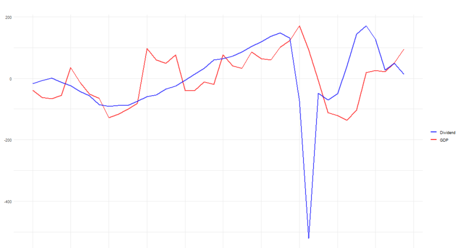
Figure 4: The Cyclical Part of Dividends and GDP for a Sample of Countries.



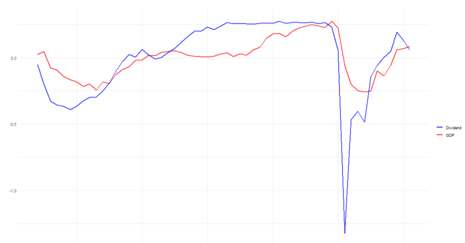
(a) Euroarea GDP and Dividends.



(b) United States GDP and Dividends.



(c) Italy GDP and Dividends.



(d) United Kingdom GDP and Dividends.

Note: The present visual representation depicts two series that showcase the cyclical components of dividends and GDP, respectively. The application of the Hamilton-filter has been employed to extract the aforementioned cyclical parts from the original data. In this context, the normalization of the axis in the visual representation may lead to a reduced degree of interpretive significance compared to traditional charts. One could argue that the axis is redundant and could be omitted from the visualization without sacrificing the content. The fundamental objective of the aforementioned visual representation is to illustrate the correlation between the cyclical component of dividends and that of GDP in a graphical manner.

As illustrated in Figure 4, the two series closely resemble each other graphically.[40] However, it is worth noting that dividends experience a more substantial decrease during times of shocks, most notably during the pandemic in 2020.

[40] The rest of the countries can be seen in Figure (12).

5.2 Approximating the lower bound of change in GDP

I compute the approximate lower bound of the change in GDP growth by scaling the change in dividend prices by a coefficient b_i for each stock market region i. The expression:

$$\mathbb{E}_t[\Delta_n Y_{it}] - 1 \geq \left(\Delta F_{i,t'}^{(n)} - 1\right) \cdot b_i \tag{8}$$

refers to the anticipated change in GDP for region i over an n-period horizon. In this equation, $\Delta_n Y_{it}$ denotes the forecasted change in GDP for the region, while b_i represents the coefficient that indicates the extent to which GDP changes in response to fluctuations in dividends. To identify an appropriate parameter b_i, I perform the following regression:

$$\Delta_1 D_{i,t} = a_{0,i} + a_{1,i}\Delta_1 Y_{i,t} + \epsilon_{i,t+4}.$$

Here, $\Delta_1 D_{it}$ signifies the change in dividends, ϵ_{t+4} denotes the regression error term, and $a_{0,i}$ and $a_{1,i}$ are coefficients to be estimated. Subsequently, I set b_i equal to the inverse of $a_{1,i}$. I conduct the regression with dividends as the dependent variable to ensure that b_i represents a lower bound in Equation (8). The rationale behind calculating $b_i = \frac{1}{a_{1,i}}$ is that differences in timing between GDP and dividend payments, as well as other uncorrelated fluctuations in GDP, can result in a decrease in the estimated value of a_{1i} and an increase in the estimated value of b_i. Consequently, this leads to a more conservative estimate for the lower bound.

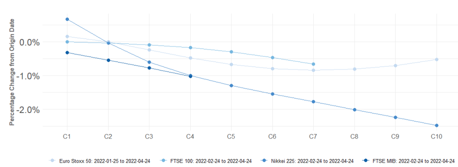
Table 4: Results and Coefficients for Different Countries

	Countries			
	EuroZone	France	UnitedKingdom	Japan
a_{1i}	1.30	1.55	1.50	1.20
Std. Error (HAC)	0.87	1.17	0.46	0.91
t value	1.50	1.32	3.29	1.33
$Pr(>\|t\|)$	0.14	0.20	0.002	0.19
b_i	0.77	0.64	0.66	0.83
N	54	35	54	53
	UnitedStates	Italy	Switzerland	Germany
a_{1i}	2.70	3.30	3.51	2.50
Std. Error (HAC)	0.71	1.87	0.78	1.27
t value	3.80	1.77	4.48	1.97
$Pr(>\|t\|)$	0.0004	0.09	0.00004	0.06
b_i	0.37	0.30	0.29	0.40
N	54	36	54	29
	Aggregated			
a_{1i}	1.83			
Std. Error (HAC)	0.32			
t value	5.66			
$Pr(>\|t\|)$	0.00000003			
b_i	0.55			
N	369			

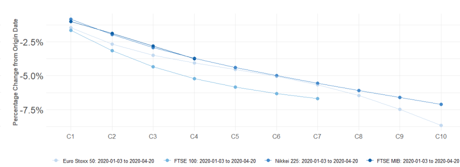
Note: The aggregated sample refers to the regression performed using all data combined. Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors are employed in the analysis.

The results, as shown in Table 4, display coefficients comparable to those of Gormsen and Koijen (2020). However, it is important to note that the estimations may be less reliable due to a shorter time series, which excludes the years 2000 and 2008 because of data unavailability.[41] The coefficients indicate that a 1% change in dividends corresponds to approximately 0.7% change in GDP for the euro area and the United Kingdom, while Italy exhibits a coefficient of around 0.3% per unit change. The United States and Germany also demonstrate notable responsiveness, with coefficients of approximately 0.37% and 0.40%, respectively. In contrast, Switzerland exhibits relatively lower sensitivity, with coefficients of about 0.29% per unit change. A N weighted mean estimate of b_i corresponds to roughly 0.33%, which is lower than the aggregate sample result of 0.55%. This variation in coefficients underscores the diverse economic dynamics across the countries under analysis.

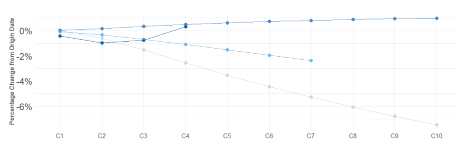
Figure 5: Lower Bound GDP Expectation Changes



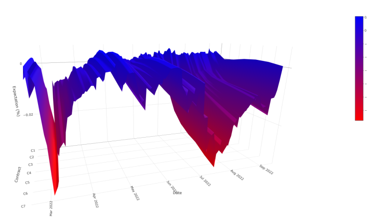
(a) 2022



(b) 2020



(c) 2010



(d)

Note: This figure illustrates the variation in lower bound GDP expectations at the time of each event compared to the stated date of the year in which the event took place. Panels (a), (b), and (c) depict the evolution of the curves over the two specified dates for the Euro Stoxx 50, FTSE 100, FTSE MIB, and Nikkei 225 respectively. Panel (d), on the other hand, presents the development of GDP expectations compared to the beginning of the year throughout 2022 for FTSE 100.

In Figure 5 I scale the change in contract prices by the acquired coefficients to obtain the implied change in lower bound GDP growth. The FTSE MIB produces somewhat spurious estimates. However, the results from Euro Stoxx 50 and FTSE 100 appear to be more robust and realistic, implying a lower bound of around 5% lower growth in the Eurozone and 3% in the United Kingdom 3-4 years after the invasion. However, while the lower bound in the Eurozone stays at -5%, the implication is that any lower growth prospects in the United

[41] The specified dates represent the best available data, and I acknowledge that some samples may be even more limited.

Kingdom disappear after 5 years.[42]

5.3 Inferring Expectations from Dividend Growth

To estimate GDP expectations accurately, one can follow the procedure outlined in Section (5.2), involving equity yields to show lower bound GDP growth expectations through scaling. However, to obtain the most precise estimate, it is necessary to consider two factors. First, the minor differences between GDP and dividends, as illustrated in Figure 4. Second, the potentially stronger correlation between the two series during periods of below-average growth, which better reflects economic distress when short-term indicators are most useful.[43] Regrettably, the dividend futures sample is too limited to effectively address these concerns. As a result, I adopt the method proposed by Gormsen and Koijen (2020), which follows a slightly different approach.

Initially, Gormsen and Koijen utilize "the long US sample" to establish a connection between dividend growth and GDP growth. This mapping is then applied to transform the dividend growth expectations from Section 4 into GDP growth expectations. I replicate this method using a comprehensive dataset provided by Shiller (2023) for the US between 1982-2020.[44] These estimates can subsequently be employed to infer GDP growth expectations for all underlying markets, based on the assumption that the relationship between GDP and dividends is roughly consistent across countries.[45] Additionally, I generate estimates that attempt to capture the "downside" relationship between GDP and dividends.

To map real GDP growth to real dividend growth, I employ the following regression:

$$\Delta_n Y_{t,i} = A_n + B_n \Delta_n D_t + e_{t+4n}. \tag{9}$$

This regression only utilizes data when $\Delta_n D_t < \overline{\Delta_n D_t}$ and thus initially focuses solely on observations where realized growth falls below average to estimate the downside correlation between GDP and dividends, which is most relevant in the context of GDP shocks. Additionally, by extending the time horizon, I

[42]More detailed tables showing the changing GDP expectations are found in Appendix 13.

[43]For a more thorough discussion of this topic, see, for example, Van Binsbergen et al. (2013).

[44]Additional data is available, extending as far back as the early 1900s; however, incorporating such data may not be beneficial due to the presence of structural breaks and significant changes in the economy over time. These transformations could render the analysis less meaningful or reliable, as the historical context may not accurately represent current market conditions or economic dynamics.

[45]This assumption can be criticized. For instance, the strong assumption that corporations worldwide would maintain the same dividend policy regardless of their institutional environment. Booth and Zhou (2017) demonstrate that institutional structure—including a country's financial system, institutions, culture, and industrial organization—is crucial in determining dividend policy. Furthermore, these factors and the subsequent relationship between dividend policy and GDP may not remain constant over time. The series has with a large degree of certainty suffered structural brakes, however, this is not something I test for.

Table 5: Estimates From Long US Sample

	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y
Estimate	0.068	0.052	0.023	0.022	0.084	0.162	0.232	0.299	0.391
Std.Error	0.002	0.001	0.001	0.001	0.001	0.002	0.004	0.003	0.000
t-value	2.717	2.025	0.824	0.730	2.629	4.868	6.490	7.334	8.181
Pr(|t|)	0.007	0.045	0.412	0.467	0.010	0.000	0.000	0.000	0.000
R-sqr	0.052	0.030	0.005	0.004	0.054	0.170	0.273	0.332	0.392
N	138.000	134.000	130.000	126.000	122.000	118.000	114.000	110.000	106.000
	2Y D	3Y D	4Y D	5Y D	6Y D	7Y D	8Y D	9Y D	10Y D
Estimate	0.310	0.282	0.191	0.090	0.055	0.255	0.349	0.305	0.267
Std.Error	0.002	0.003	0.003	0.003	0.004	0.002	0.000	0.000	0.001
t-value	8.703	7.378	3.865	1.669	1.009	4.836	5.929	4.817	4.403
Pr(|t|)	0.000	0.000	0.000	0.100	0.317	0.000	0.000	0.000	0.000
R-sqr	0.527	0.445	0.180	0.040	0.015	0.259	0.344	0.257	0.224
N	70.000	70.000	70.000	69.000	69.000	69.000	69.000	69.000	69.000

Note: The presented table illustrates the slope coefficient B_n resulting from a regression analysis of GDP growth onto dividend growth at varying horizons (n), under different conditions. The coefficient is estimated using a 2-year growth period in the sample spanning from 1982 to 2019. The analysis on observations where realized dividend growth falls below the time-series average is in the lower part of the table. Real dividend growth is used for the S&P 500, while real GDP growth in the United States is used for GDP growth. Observations are conducted on a quarterly basis. The presented standard errors are based on the HAC.

can lessen the impact of minor asynchronicity and the lack of data in only one unique sample.

Table 16 presents the slope coefficient B_n obtained from regression (9) of GDP growth onto dividend growth at various horizons (n) under the two conditions. Using the US sample from 1982 to 2019, I estimate B_n for periods up to 10 years, which correspond to the longest maturity available. The baseline estimation indicates that during downturns, dividends tend to move approximately three to four times more than GDP, as shown in Table 16. This finding suggests that dividend payouts could serve as a leading indicator of economic distress, providing information for investors and policymakers when assessing the state of the economy and making informed decisions.[46]

The 1-year growth estimates are excluded from Table 16, as GDP and dividends are not entirely synchronized over brief time horizons.[47] Upon examining the unconditional relationship between GDP and dividends, the slope coefficient for shorter horizons is more than half as large, implying a weaker positive correlation between GDP and dividend growth. This observation suggests that the hypothesis of a stronger downside relation between dividends and GDP has some merit, but also that factors other than GDP growth, such as changes in corporate policies or industry-specific trends, may exert a more substantial influence on dividend payouts during relatively stable economic conditions.

After estimating the relationship between GDP and dividends, GDP growth can then be forecasted as follows:

$$E_t[\Delta_1 Y_{i,t}] = A_i + B_2 \beta_1^D e_{i,t}^{(2)} \tag{10}$$

The approach utilizes the same estimate of B_n for all countries, which is derived from the US data. It is important to note that the estimates produced are

[46]Interestingly, the two estimates below and above the mean GDP seem to converge when using longer horizons. This observation implies that, over extended periods, the relationship between GDP and dividends may stabilize, regardless of the prevailing economic conditions. This information could be helpful for long-term investors when evaluating the potential returns from dividend-paying stocks.

[47]As demonstrated in Figure 4. Additionally, the shortest horizon is less pertinent to our analysis due to the "pull-to-realized"-effect, which is extensively discussed in section 7.2.

based on a forecasting model that utilizes historical data, and given the highly volatile and dynamic world we live in, there is a possibility that historical relationships could change, leading to uncertainty in these estimates, as previously discussed.[48]

A Brief Discussion on the Complexity of Inferring GDP Expectations

The methodology employed by Gormsen and Koijen (2020), as well as in this study, which utilizes equity yields to infer GDP growth expectations, presents certain limitations that necessitate caution. Two primary concerns associated with this approach are identified:

Firstly, predicting GDP growth based on anticipated equity yields can be a contentious endeavor. While there is some support in financial theory and empirical evidence, as illustrated by Van Binsbergen et al. (2013) and in Section 4, the relationship between investor dividend forecasts and their ex-ante GDP forecasts can be met with skepticism. This doubt stems from the discrepancy between realized dividends and ex-post GDP, potentially resulting in a noisy forecast of implied GDP growth expectations, or even pure noise at its worst. As previously discussed, it is a strong assumption that market participants' actions are indicative of their underlying future expectations; some transactions may arise from systematic hedging processes or similar events. Furthermore, it is worth questioning the extent to which the selected stock indices, comprising the largest listed companies in a region, accurately represent the economy. For instance, during the COVID-19 pandemic, the hardest-hit sectors were travel, leisure, and restaurants, often dominated by small business owners, which would not be reflected in an index encompassing the 50 largest and most traded companies in Europe (Euro Stoxx 50).[49]

Secondly, this approach necessitates the extrapolation of future trends from historical data, relying on the assumption that the underlying structural variables in the economy remain constant. It is plausible that significant global events, such as the Ukrainian invasion, the COVID-19 pandemic, the Euro crisis, or the Great Financial Crises, could fundamentally alter the underlying data-generating process, rendering historical data inadequate for predicting future outcomes.[50] The magnitude of any error resulting from this method is likely to be more significant when addressing higher-order economic variables, such as GDP, as opposed to solely examining changing dividend expectations. As a result, it is crucial to exercise caution when interpreting outcomes derived from such techniques and to consider potential limitations and biases inherent

[48] A example of the difference between the two techniques discussed in Sections (5.3) and (5.2) can be found in Figure 13

[49] However there are potential solutions to this problem. Utilizing the method discussed in Appendix 9.3 one would be able to acquire an even more granular view of dividend growth expectations. For example, comparing sectors through the lens of company-specific stock options.

[50] Although this assumption is partially accounted for in my analysis through limiting my sample and using daily observations instead of quarterly, like those of Gormsen and Koijen, when estimating changing dividend growth expectations.

in the approach.

In light of these concerns, it is essential to recognize that the findings presented in this study should be interpreted with care. While the methodology provides valuable insights into the relationship between equity yields and GDP growth expectations, the results ought to be considered as one element within a broader analysis that accommodates additional factors and potential sources of uncertainty.

6 Dividend Price Dynamics in Market Downturns and Recoveries: Implications for Asset Pricing Theories

During the initial phase of a market downturn, as investigated by Gormsen and Koijen (2020) — which occurred between February 19 and March 5 — researchers observed a decline in long-term dividend prices, while the short-end of the term structure exhibited smaller movements. This reduction, a significant contributor to the overall market decline, primarily resulted from an increase in discount rates rather than a decrease in expected dividends. As some growth is anticipated, it is likely that the projected decline in the expected value of short-term dividends would surpass the anticipated decline in the expected value of long-term dividends, making discount rate changes the primary suspect of the price decrease. [51] An increase in discount rates is commonly observed during periods of financial stress, driven by fluctuations in the SDF, of which the COVID-19 pandemic was one as evidenced by Baker et al. (2020).[52]

The SDF represents the relationship between an asset's risk and return, capturing the notion that investors demand higher returns during times of economic uncertainty. In such periods, investors perceive investments as riskier, leading to increased discount rates. It is important to note that the beta coefficient, which represents the systematic risk of an asset, may remain constant over time. In this case, changes in discount rates are driven exclusively by fluctuations in the SDF, rather than changes in the beta coefficient itself. As an economic crisis unfolds, growth expectations are significantly revised, often becoming more pessimistic or uncertain. This change in outlook directly impacts investor sentiment and risk appetite. Consequently, the prices of both short- and long-term dividends typically experience a substantial drop. This decline occurs because investors become more cautious and risk-averse during a crisis, requiring higher returns to compensate for the increased risk associated with holding these assets in uncertain times. The SDF plays a crucial role in explaining the variation in discount rates during periods of economic distress, highlighting the connection

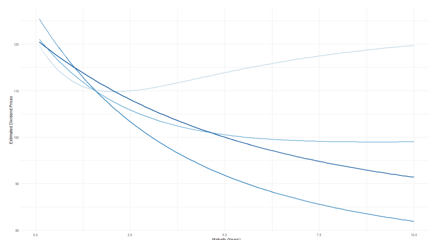
[51] However, this has been contested. For example, Böni and Zimmermann (2021) finds, using Gordon's constant growth model, that during the COVID-19 pandemic, the impact of changes in the discount rate on stock returns was less significant than changes in the long-run implied growth rate.

[52] The SDF is thoroughly explained and derived in its simplest form in the Appendix 9.4.

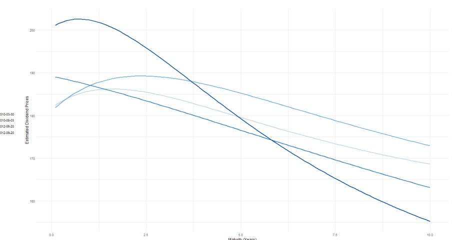
between increased risk perception and higher returns demanded by investors, which in turn leads to lower prices for assets that provide long-term dividends.

Subsequently, as the stock market begins to recover, long-term dividend values usually increase, while immediate dividend values continue to decrease. Notably, using dividend futures I can visualize this through long-term dividend values which revert to pre-crisis levels, signaling a normalization of the discount rates applied to these dividends. Figure 6 illustrates that this pattern is common across most markets during periods of financial turmoil.

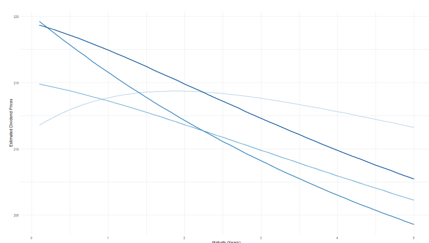
Figure 6: Harmonizing Market Valuation with Dividend Price Dynamics



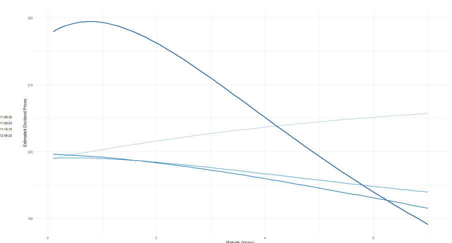
(a) Euro Stoxx 50.



(b) Nikkei 225.



(c) SMI 30.



(d) FTSE 100.

Note: The examples above stem from the Euro Crises. The Nelson-Siegel function is fitted to the term structure of dividend prices under the restriction that the sum of all dividend prices matches the market price. For each row of input price data, the market price is calculated as the sum of all dividend prices. The Nelson-Siegel parameters are estimated by minimizing the Sum of Squared Residuals (SSR) while ensuring that the sum of the fitted curve values is approximately equal to the market price (within a small tolerance value). The resulting parameters are then used to generate the term structure of dividend prices for a given set of maturities.

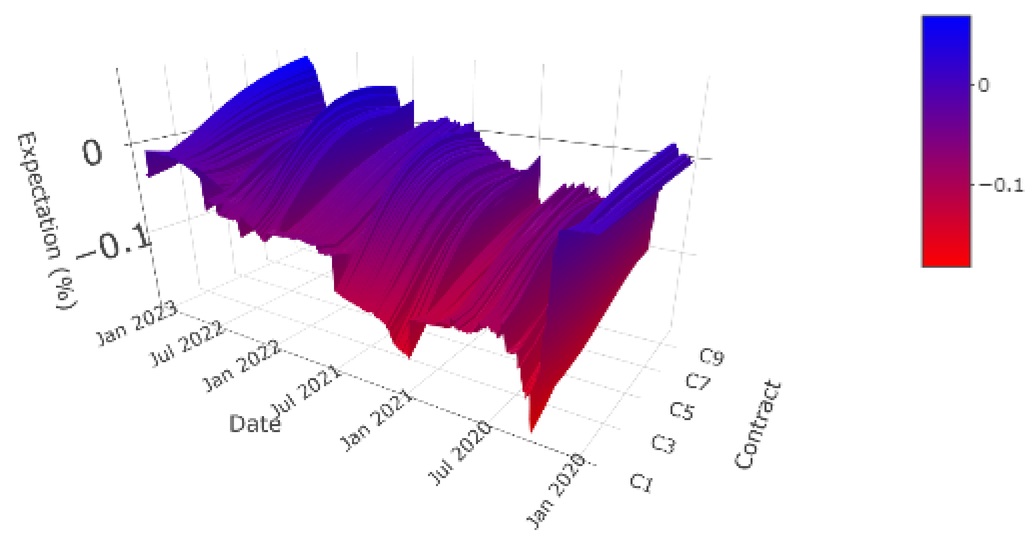
These observations have implications for asset pricing theories, especially in the context of identifying economic disruptions that cause volatility in asset prices. Traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM) and the Dividend Discount Model (DDM), fail to account for the complexity of market dynamics observed during crises. The observed patterns in dividend prices during downturns and recoveries suggest that alternative models, such as those incorporating for example, time-varying risk premia or behavioral components, might be better suited for capturing the evolving risk perceptions of investors during such periods.

Although pinpointing disruptions may be challenging, unique shocks—such as the global pandemic or the Russian invasion of Ukraine—offer opportunities for identification due to the distinct nature and timing of the events.[53] While uncertainties surrounding the long-term effects of any crisis remain, it is generally reasonable to suggest that short-term economic growth consequences are more severe than those occurring over an extended period.

Additionally, the initial drop in the overall market during the outbreak, as demonstrated in Figure 3, combined with the modest response to short-term dividend prices, indicates that even moderate disruptions to short-term expectations can result in significant and lasting changes to expected excess returns. This suggests that investors perceive shocks to near-future dividends as risky, potentially accounting for the downward-sloping equity term structure and the increased returns for firms generating near-future dividends.

Figure 6 displays the estimated dividend prices for various maturities, with the term structure of dividend prices adapted to the functional form proposed by Nelson and Siegel (1987), subject to the constraint that the cumulative price of all dividends equals the market value.

Figure 7: Recovery of Expectations Over The Long Term Since 2020 For Euro Stoxx 50



In conclusion, these findings provide insights into the factors driving the stock market's collapse and subsequent recovery and their implications for pric-

[53] Identifying the precise economic shocks responsible for inducing fluctuations in prices often presents a challenge, as empirically exemplified by the work of Cutler et al..

ing theories. The patterns observed in dividend prices during market downturns and recoveries highlight the need for a more nuanced understanding of the underlying mechanisms driving asset prices and the potential benefits of incorporating time-varying risk premia or behavioral components into asset pricing models.

7 The Dividend Futures Market, Liquidity, and Idiosyncrasies

7.1 Liquidity and Trading Volumes

It is vital to reexamine the validity of inferring stock market expectations through dividend futures prices, particularly concerning liquidity and trading volume aspects.

Evaluating liquidity and dividends can be challenging, as it entails various methodologies and is often difficult to quantify.[54] Schestag et al. (2015) argue that no single method or strategy for assessing liquidity has been consistently employed in previous research; rather, a range of approaches has been utilized. Lesmond (2005) explore different liquidity metrics, including ILR, LOT, and Bid-Ask spread.[55]

With this in mind, the endeavor is further complicated by the fragmented data on dividend futures, where obtaining information on the OTC market, the primary market for such instruments, proves challenging. As Mixon and Onur (2016) illustrate in their overview, utilizing regulatory reporting data from that period, the only genuinely active listed futures market was the Euro Stoxx 50 market. Furthermore, they conclude that market activity is limited beyond the initial few years of dividends, with infrequent customer-involved OTC transactions.[56] For simplicity and data availability, this discussion focuses on the actual reported exchange transaction volume in the markets examined and the bid-ask spread for markets with accessible data.

[54] The primary reason for this difficulty is the scarcity of data required to quantify the liquidity of illiquid markets. For instance, in the dividend futures market, Van Binsbergen et al. (2013) used proprietary data from banks and thus was able to study the large swath of OTC trades being conducted.

[55] These distinct measures, most often discussed in the similar fixed income market, are discussed in the Appendix.

[56] An example of this issue is, for instance, Van Binsbergen et al. (2013), which examined a comprehensive set of indicative dividend swap prices but could not provide context regarding the actual transactions occurring in these markets.

Table 6: Summary of Trading Characteristics for Ten Futures Contracts

	EU			France			Japan		
Contract	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)
C1	2443.00	159187.05	13.68	1859.95	30543.70	2.56	47.95	10073.00	0.88
C2	5081.88	178257.25	2.69	1798.02	22564.46	3.28	46.99	7552.80	1.03
C3	4406.17	140437.24	9.95	1473.28	18402.30	3.91	42.56	4242.87	1.20
C4	3007.16	90962.01	3.51	1118.18	9584.05	4.35	34.40	2304.03	3.35
C5	2155.41	73251.90	5.34	1071.19	9131.58	4.72	27.65	1523.87	6.82
C6	1238.25	48477.78	2.85	-	-	-	22.43	931.21	6.83
C7	621.61	26515.12	3.31	-	-	-	14.46	537.66	6.75
C8	370.67	15285.21	4.93	-	-	-	9.67	338.84	7.64
C9	216.77	9322.11	6.4	-	-	-	11.99	172.14	7.58
C10	171.34	7596.73	7.37	-	-	-	11.12	78.96	8.56
	Italy			Switzerland			United Kingdom		
Contract	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)
C1	22318.12	43839.01	0.47	17.66	1067.81	1.45	558.79	84228.07	1.27
C2	2093.72	3252.19	0.98	28.81	815.53	2.89	728.22	77841.75	2.46
C3	6.39	30.07	1.22	17.28	428.37	3.64	585.49	47641.93	2.31
C4	0.42	3.02	2.96	7.99	174.55	4.60	470.85	28501.00	2.56
C5	-	-	-	5.73	84.86	4.50	90.30	11294.89	4.33
C6	-	-	-	-	-	-	254.29	7731.08	3.74
C7	-	-	-	-	-	-	92.45	2238.68	3.95
C8	-	-	-	-	-	-	-	-	-
C9	-	-	-	-	-	-	-	-	-
C10	-	-	-	-	-	-	-	-	-

Note: The table presents averages across the entire sample period. For instance, Open Interest signifies the average daily amount of outstanding contracts. Volume refers to the daily average of traded contracts, while bid-ask spread represents the average daily percentage discrepancy between buying and selling prices in the market. A table showing the development from 2020 going forward is found in the Appendix 23.

Table (6) presented in this study provides an extensive overview of trading activity across six major markets - the EU, France, Japan, Italy, Switzerland, and the United Kingdom. Data regarding the German Dax Dividend contracts is unavailable from Refinitiv Eikon, but has very small volumes according to Mixon and Onur (2016).[57] The table highlights the mean trading volume, open interest, and bid-ask spreads for ten different contracts, serving as a valuable resource for researchers and investors.

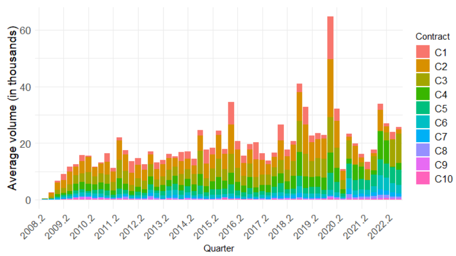
A notable observation is that trading volume and open interest generally decrease as contract maturity increases, suggesting that earlier contracts are more liquid and actively traded. Additionally, the bid-ask spread tends to increase with the contract number, possibly due to lower liquidity. However, it is important to note that markets for contracts C5 through C10, maturing 5 to 10 years into the future, are not available for all markets, limiting the generalizability of these observations.

Another trend evident from the Table (6) is that the mean trading volume and open interest are generally higher in the EU and France markets, indicating increased market activity and liquidity in these regions. Japan also exhibits the lowest bid-ask spreads, signifying high competition among market makers in that market. However, it is crucial to recognize that bid-ask spreads can be influenced by various factors, including market structure and regulation, and cannot be solely attributed to liquidity differences across markets.

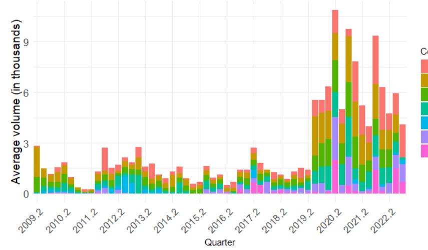
As shown in Table 6 and Figure 9, during periods of high volatility, such as GDP shocks during the pandemic, the bid-ask spread tends to widen. This also holds true for actual on-exchange transaction volume. This could pose a

[57]The US data had several contracts missing in the Refinitiv Eikon database, making me unable to stitch together anything of use.

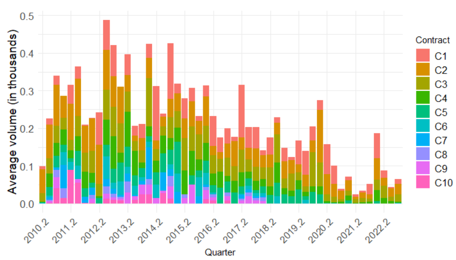
Figure 8: Average On Exchange Trading Volumes per Market



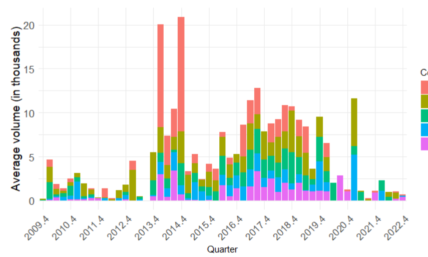
(a) Euro Stoxx 50



(b) FTSE 100



(c) Nikkei 225



(d) CAC 40

Note: The bar chart represents the average volume (in thousands) of contracts C1 through C10 for each quarter across the entire sample period. The volume for each contract is stacked, meaning the total height of each bar represents the combined average volume for all contracts in that quarter. The colors differentiate each contract, with C10 at the bottom and C1 at the top of each bar. Note that the data for each contract is averaged over the sample period, providing a summary view of contract volumes over time. For a corresponding graph showing the open interest, please refer to the figure in Appendix 16.

significant challenge for the method: if actual transactions and liquidity diminish during moments when the method is relied upon to generate viable forecasts for future dividend streams, it presents an inherent issue. However, this problem appears to be less prevalent for longer maturities, as seen in Figure 9, where contracts maturing in 6 and 8 years, corresponding to Figure (16c) and (16d), exhibit smaller variance compared to shorter maturities and tighter bid-ask spreads during crises. Moreover, examining the tables in the Appendix, such as Table 17, there is no apparent decrease in the mean daily traded volumes during years of significant financial distress.[58] This is encouraging and aligns with the findings of Table 6, which show healthy spreads across most markets and contracts.

The observed widening of the bid-ask spread and reduction in transaction volume during periods of high volatility raises concerns about the reliability of using dividend futures as an indicator of future dividend and GDP growth expectations. An increase in spreads, representing the cost of trading a contract, can make entering or exiting positions more expensive for traders, potentially discouraging trading and decreasing liquidity. This, in turn, may lead to less

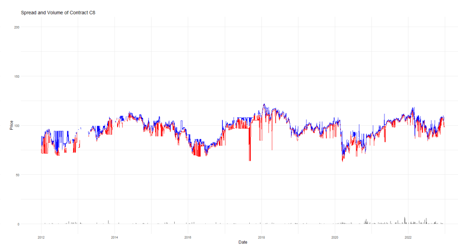
[58] However it should be noted that Italy (FTSE MIB contracts) had a decrease in activity during the period characterized by the Euro crisis.

Figure 9: Spread and Volume across various maturities of Eurostoxx 50 Dividend Futures

(a) Contract maturing in 2 years.

(b) Contract maturing in 4 years.

(c) Contract maturing in 6 years.



(d) Contract maturing in 8 years.

reliable information on market expectations for dividend growth.

Furthermore, reduced liquidity in times of high volatility can hinder investors' ability to capitalize on arbitrage opportunities, which require sufficient liquidity and accurate price information. As liquidity diminishes, executing trades becomes more challenging, and bid-ask spreads may widen further, causing additional market distortions. However, this seems to be less of a problem in most markets, with liquidity often increasing during turbulent years.

Despite these concerns, evidence suggests that longer-maturity dividend futures contracts may be less susceptible to market volatility. This resilience could stem from their reduced sensitivity to short-term market fluctuations and their ability to provide more stable estimates of expected future dividend growth. Additionally, longer-maturity contracts may be less influenced by speculative trading, which can exacerbate volatility and widen bid-ask spreads.

In conclusion, the challenges posed by bid-ask spread and liquidity issues during periods of high volatility present potential obstacles to using dividend futures as a tool to predict GDP growth. However, evidence suggests that these problems are relatively minor in most well-established markets, while lesser-known markets face more significant difficulties in this regard. Further research is necessary on this subject, as studies such as those by Gormsen and Koijen (2020) and Van Binsbergen et al. (2013) rely on proprietary data from banks, which are assumed to include OTC transactions not available in the data provided by Refinitiv Eikon.[59]

One potential approach for researchers and practitioners to reduce uncertainty regarding quotes is to incorporate the method outlined in Appendix 9.3, which enables the inclusion of more data points into the created term structure.[60] Due to time constraints, I have not been able to pursue this avenue myself.

7.2 Idiosyncrasies

The approach of utilizing dividend futures to interpret the market's shifting dividend and GDP expectations is constrained in the shortest maturity by several factors, and in longer maturities by a few, including liquidity concerns.[61]

Firstly, far-dated maturities are influenced not only by macro variables but also by the issuance of structured products. The dividend overhang from these products is primarily concentrated in the three to seven-year maturity range, although it persists up to the maximum maturity of approximately 10 years, as demonstrated by Bunsupha and Liao (Working Paper).[62] However, the overhang also impacts the near end of the curve. Any deviation, such as overvaluation of near-dated dividends, could encourage investors to initiate dividend steepeners to profit from the low implied dividend growth rate, which may counteract the effect.[63] As the effect of structured products overhang is more significant for longer maturities, it typically results in increased inexpensiveness and demand of implied dividends with longer maturity, creating a downward sloping curve, and may obscure the analysis of expected dividend levels for far-dated maturities.[64]

[59] After investigation and inquiries to Refinitiv Eikon regarding data quality and potential errors, Refinitiv Eikon support was unable to confirm any errors in the data, despite considerable investigation time. Data from 2021 onwards appears to be more "unstable," with some contracts experiencing large fluctuations. Differences in data quality can be observed when comparing bid-ask spread discrepancies between Gormsen and Koijen (2020) paper and the present study, such as for the Euro Stoxx 50. A more thorough discussion on this is found in Appendix 9.6.

[60] Options face many of the same issues as dividend futures but are a more popular and well-known instrument among investors.

[61] However, examining the change in prices during shocks, as in this paper, mitigates most of these issues, since we can adhere to a ceteris paribus notion.

[62] The paper by Bunsupha and Liao (Working Paper) reevaluates the downward-sloping term structure of equity risk premium and suggests a demand-based pricing model. They claim localized market participation and equity derivative products partially explain the term structure and time variation of implied equity dividends. The authors show that major equity indices' implied dividend term structures respond to flows from equity-structured product issuance.

[63] A steepener in this context implies that the investor short sells near-dated dividends and buys far-dated dividends.

[64] As spot declines, the long position in dividends of structured product sellers increases, leading to an increase in the maturity of auto-callables (structured product with predescribed call dates) and a need for capital-protected notes (most common is a package of bonds and put-options) sellers to hedge by selling futures and increasing their dividend position (See e.g., Baeston (2011) for an introduction to these kinds of products). Investment banks that sell structured products are structurally long implied dividend risk and may sell cheap implied dividends to hedge funds to allow for further structured product sales.

Secondly, regardless of the frequency of dividend payments, the shortest-dated maturities of dividend futures effectively transform into a 'cash-basket' within the second quarter of their expiration year. This metamorphosis essentially shifts the nature of the dividend future, rendering it comparable to an interest rate instrument, a phenomenon that can be referred to as a "pull-to-realized" effect.[65] In situations where a company declares an interim dividend, it's commonplace for the interim and final dividends to be announced simultaneously, as seen in Japan, or for the final and larger dividend to be announced in the first half of the year, as practiced in the United Kingdom. With respect to quarterly dividend payments, approximately half of these dividends would have been declared by mid-year, thereby providing substantial clarity into the outstanding dividends and reducing the equity risk. This circumstance potentially undermines the efficacy of the shortest-dated contracts as a means of interpreting market expectations due to the introduction of substantial nonlinearities into the relationship.[66]

The "pull-to-realized"-effect is amplified by the convergence of implied dividends in the third quarter of the year prior to expiration. By this point, half of the calendar year's results are known, enabling investors to place greater trust in analysts and their own expectations. This is because dividends are paid from the previous year's earnings by the third quarter of the preceding year, with some international differences. However, the "pull-to-realized"-effect occurs later for FTSE companies that pay interim dividends. The calendar year dividend payout for a company with interim dividends consists of final and interim dividends from different financial years, whereas, for a company with annual dividends, it is based on just one financial year. Consequently, the "pull-to-realized"-effect is delayed as earnings from a later period must be considered. This effect becomes less problematic when examining indexes since market estimates consistently reflect the macroeconomic picture. Shocks to dividend payments, such as government restrictions in 2020 or 2008, can override the "pull-to-realized" effect.[67]

Additional "non-fundamental" factors influencing expected dividend levels include survivorship bias and changes to the indexes underlying the derivatives. Generally, these factors benefit index dividends as underperforming companies that reduce dividends are more likely to be removed from an index than those that increase dividends. Nonetheless, index membership changes pose risks. A company's size and dividend yield affect the index divisor, as shown in Section 2.1, and the impact of changing membership on an index's dividend yield is not always evident and may obscure underlying relationships over time.[68] This

[65]This is particularly relevant in Europe, where most companies distribute annual dividends, typically announced by the end of the first half of the year.

[66]To illustrate this point, shortest-dated maturities typically display minimal variance until a sudden shift occurs. For example, during crises like the COVID-19 pandemic, these short-term components maintain stability until either dividends are restricted, or investors start to anticipate that companies might revoke their dividends.

[67]Notably, this effect does not preclude future value changes, as demonstrated by BP's dividend cancellation in 2010, which caused a rapid shift in FTSE dividends.

[68]For instance, the frequency of dividend payments can influence index payout, as evidenced by for example the September 2009 Euro Stoxx 50 re-balancing, when a company with

is of importance when estimating historical relationships between GDP and dividends, and may have obfuscated the results somewhat.

These "non-fundamental factors" complicate interpreting futures prices and hinder drawing clear inferences. It is essential to consider these factors when analyzing dividend futures data and related empirical work, as neglecting them could lead to inaccurate conclusions about market expectations and economic conditions. The dividend future literature and my paper may not have adequately addressed these factors, potentially affecting the validity of their results and derived implications.

When examining the information contained in dividend futures prices, researchers and market participants should carefully consider the impact of survivorship bias, index membership changes, and other non-fundamental factors on the level of expected dividends. In the case of my paper, it may have had an effect on the estimated historical relationships, but less so on the actual price effects measured in the market. By acknowledging these effects it becomes possible to obtain a more accurate and nuanced understanding of market expectations and the driving forces behind them.

Furthermore, it is essential to recognize that the factors mentioned above can interact with and influence each other in complex ways, which may further obscure the true relationships among dividends, market expectations, and macroeconomic variables. By developing a comprehensive understanding of these factors and their interplay, researchers can better navigate the challenges associated with analyzing dividend futures data and contribute to a more reliable and insightful analysis of market expectations and their implications for economic policy and decision-making.

7.3 Dividends during crises

Dividends exhibit unique properties during times of crisis that distinguish them from other financial instruments, such as bonds. These characteristics stem from the fact that dividends are "sticky" to the downside, meaning that even during a crisis, dividend payments tend to remain stable, and companies are typically reluctant to cut them (See for example: Kim et al. (2017)). However, in severe downturns, companies may reduce their dividends significantly.

The behavior of dividends during a financial crisis is further influenced by a technical imbalance in the dividend market. Dividend payouts are typically maintained at a level well below 100% of earnings, allowing companies to preserve their dividend payments even in the face of declining earnings. However, during periods of extreme financial distress, such as the 2008 credit crisis, government-imposed constraints on financial institutions resulted in implied dividends underperforming the spot market. This technical imbalance may precipitate a collapse of near-dated implied dividends, leading to a diminished beta (to spot dividends) of far-dated dividends. Consequently, as the spot market declines, the implied dividend growth rate experiences an increase, and vice

quarterly dividends entering the index boosted dividend futures and swaps.

versa. This phenomenon contrasts with the pre-Lehman bankruptcy period, during which rising equity markets encouraged investors to anticipate increasing dividend yields.[69]

In contrast, bonds, particularly government bonds, provide a different perspective on market expectations during times of crisis. Yield curves derived from government bonds can indicate market expectations of future interest rates and inflation, which are closely related to economic growth. However, at the ZLB, the usefulness of bonds as a forecasting tool becomes more limited, as unconventional monetary policies can distort the yield curve, making it challenging to draw clear inferences about market expectations (see e.g., Swanson and Williams (2014)). This is however not a problem when utilizing the dividend futures as forward equity yields are not bounded above and thus will not be susceptible to the same non-linear effects as the relationship between growth and interest rates.

Despite these complexities, overall, while dividends generally do not underperform spot during a crisis, their behavior can be influenced by technical imbalances in the dividend market and government regulations.[70] When analyzing market expectations and underlying economic conditions, it is essential to consider the limitations of both dividends and bonds as forecasting tools, especially at the lower bound.

8 Conclusion

In periods of financial and economic turbulence, acquiring timely, forward-looking insights into the projected economic trajectory is essential for both policymakers and market participants. This study establishes that dividend futures can be used in achieving this objective. By examining dividend futures across a spectrum of countries, each with unique dynamics, this study provides insights into the lower bounds of expected dividend and GDP growth. It illustrates that even smaller, less actively traded markets can offer valuable inferences about market expectations for these variables.

This research contributes to the literature by reinforcing the value of dividend futures as tools for deriving forward-looking estimates during periods of uncertainty and crisis. It is also, to the best of my knowledge, the first study to explore the impact of war on dividends and GDP growth expectations using dividend futures. These findings underscore the importance of liquid derivative contracts when applying methods that rely on the relationship between the prices of these contracts and economic variables.

[69]Fodor et al. (2017) employs forward-looking implied dividend information from option prices to predict dividend cuts and omissions amidst the 2008-2009 financial crisis. Incorporating the technical imbalance that contributes to the collapse of near-dated implied dividends, they highlight the importance of the beta (to spot dividends) of far-dated dividends in this scenario. Additionally, they reveal the contrasting dynamics of implied dividend growth rates during the pre-Lehman bankruptcy period implied by the options.

[70]Technical imbalances such as hedging needs and effects from previously mentioned structured products in Section 7.2.

For instance, compared to the SMI 30 or FTSE MIB, the Euro Stoxx 50 will generate more accurate and precise estimates due to its higher trading volume and liquidity. However, these differences did not significantly impact my results. As an empirical researcher, data availability is a constraint. If dividend futures gain wider acceptance and become more liquid instruments globally, future studies could provide more robust estimates and draw conclusions about additional regions.

Looking ahead, research should focus on exploring the broader adoption of dividend futures internationally, the use of options to infer market expectations, and the time-varying factors which influence the price of dividends. This would further enrich our understanding of the interrelationships between forward equity yields, economic growth, and market reactions to crises. In doing so, the study will help guide policy decisions and financial strategies during periods of economic turbulence.

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9 Appendix A

9.1 D_t^* The Approximate Index for Cumulative Dividends

In order to determine daily dividends for contracts lacking the underlying index information from Refinitiv Eikon, I procure daily return data, encompassing both gross return (inclusive of dividends) and price return (exclusive of dividends). Subsequently, I calculate cash dividends as the disparity between the returns with and without dividends, multiplied by the preceding index value. Given that dividend futures prices revolve around a complete calendar year of dividends, I employ the dividends from the previous year as the numerator in the subsequent equation:

$$D_t = (R_{t,Gross\,Return} - R_{t,Price\,Return}) \times I_{t-1}.$$

Here, D_t denotes the daily dividend, $R_{t,Gross\,Return}$ represents the daily return comprising distributions, $R_{t,Price\,Return}$ signifies the daily return devoid of distributions, and I_{t-1} stands for the lagged index value at time $t-1$.

For example, when calculating equity yields on December 15th, 2019, I use the sum of dividends disbursed between December 16th, 2018 and December 15th, 2019 as the numerator. This method mitigates concerns associated with seasonality, as both the dividend futures price and the prevailing dividend level correspond to an entire year of dividends.

9.2 Liquidity measures

Amihud (2002) devised a measure of illiquidity, ILR, which constitutes a ratio of two variables: a security's absolute daily return and its daily dollar volume. This measure is computed as an average over the period in question. A key advantage of this metric is its simplicity, as the required data can be readily obtained from databases. However, the measure is influenced by the fact that as the traded volume approaches zero, ILR converges toward infinity as pointed out by Fredrik Bonthron and Mannent (2016), making it less useful for studying dividend futures as some market's volume often tends to zero.

Lesmond (2005) developed the LOT model, which is predicated on the number of zero returns observed by Lesmond et al. (1999). A drawback of this measure, however, is that data for at least one month is necessary to perform the calculation. Another limitation is that if zero returns transpire for over 80 percent of the period, the measure becomes inapplicable. This would have been a useful tool in my paper. However, time constraints stopped me from proceeding.

The Bid-Ask spread measure is employed by examining the evolution of transaction costs, achieved by gauging the density of the difference between the buy and sell price of a bond as pointed out by Fredrik Bonthron and Mannent (2016). In calculating the measure, either the average of the best actionable buy and sell prices can be utilized, or an absolute amount can be employed. Nonetheless, a disadvantage of this measure is that it depends on actionable prices. In the context of less liquid markets, such as the Swedish bond market discussed in the paper or the dividend futures prices of more obscure markets such as Switzerland, prices are indicative rather than actionable, which could engender an inaccurate measure. The Bid-Ask spread measure was implemented in the paper.

9.3 Option implied Dividend Growth

In Bilson et al. (2015), the researchers establish the practicability of inferring the options-implied dividend yield, denoted as $y^d_{t,n}$, on expected returns. The same procedure may be possible but with dividend, and therefore GDP growth expectations. Utilizing the put-call parity principle, the dividend yield can be expressed as:

$$c_{t,n} - p_{t,n} = S_t e^{-ny^d_{t,n}} - Ke^{-ny_{t,n}} \tag{11}$$

In this equation, $c_{t,n}$ and $p_{t,n}$ symbolize the prices at time t of a call and put option, respectively, with a maturity n on the stock index S_t. Both option contracts share the strike price, represented by K.

To determine $y^d_{t,n}$, the equation is restructured as follows:

$$y^d_{t,n} = (1/n) * ln\left(\frac{c_{t,n} - p_{t,n} + K * e^{-n*y_{t,n}}}{S_t}\right), \tag{12}$$

The maturities n, corresponding to the inferred dividend yields $y^d_{t,n}$, coincide with the available option maturities at time t. In agreement with Bilson et al. (2015), a Nelson and Siegel (1987) interpolation can be applied to all observed $y^d_{t,n}$ to recover the entire maturity range of options-implied dividend yields. As a result, instead of assuming a constant slope between two observed $y^d_{t,n}$, a smooth Nelson and Siegel interpolation can be fitted for each time point t:

$$y^d_{t,n} = \beta_0 + \beta_1 \frac{1 - e^{-\lambda_t n}}{\lambda_t n} + \beta_2 \left(\frac{1 - e^{-\lambda_t n}}{\lambda_t n} - e^{-\lambda_t n}\right), \tag{13}$$

By employing the full maturity spectrum of $y^d_{t,n}$, the associated values for a dividend-paying asset can be determined.

Using the entire maturity range of $y^d_{t,n}$, the corresponding values for $g^Q_{t,n}$ can be computed. Following van Binsbergen et al. (2012), I designate $P_{t,n}$ as the price of a asset that distributes all future dividends up to $t + n$:

$$P_{t,n} := \sum_{i=1}^{n} S_{t,i}. \tag{14}$$

The "present value" representation of put-call parity is thus:

$$c_{t,n} - p_{t,n} = S_t - P_{t,n} - Ke^{-ny_{t,n}}. \tag{15}$$

By subtracting Equation (11) from Equation (15) and solving for $P_{t,n}$, I derive:

$$P_{t,n} = S_t \left(1 - e^{-ny^d_{t,n}}\right). \tag{16}$$

In conclusion, the term structure of $D^Q_{t,n}$ aligns as:

$$F_t^{(n)} = (P_{t,n} - P_{t,n-1})e^{ny_{t,n}}, \tag{17}$$

Utilizing this approach to obtain a greater number of quotes for the dividend term structure may prove to be advantageous in maintaining the short end of the curve at a realistic level, particularly in less liquid markets. This method addresses the challenges associated with market illiquidity, which may lead to inconsistencies in the pricing of the options-implied dividend yields. As a result, investors can gain a more accurate representation of the market's expectations regarding dividend yields and their associated term structures.

Moreover, by incorporating a larger set of quotes and interpolating the data using the NS-model methodology, the technique would generate a smoother term structure and more realistic, thereby reducing the impact of any effects introduced by lacking price quotes. Consequently, the extrapolated curve offers a more reliable and robust estimation of the options-implied expected dividend growth rates.

In summary, employing this method to gather an increased number of quotes for the dividend term structure enables a more precise estimation of the options-implied dividend yields and their associated term structures. This approach, I believe, is particularly beneficial in less liquid markets. It would ensure, especially in the short end, that the curve remains at a realistic level, ultimately providing investors with a more accurate and reliable representation of the market's expectations.

9.4 Stochastic Discount Factor

The Stochastic Discount Factor (SDF) can be explained and derived, with the help of Cochrane (2009), in the following manner: Presume an investor who can purchase and sell a quantity of an asset at a price p with a payoff of x_{t+1}. The initial consumption level can be represented as e, while the quantity of assets the investor chooses to purchase can be denoted as ξ. Consequently, the problem can be formulated as:

$$\max_{\xi} u(c_t) + E_t[\beta u(c_{t+1})]$$

subject to: $c_t = e_t + p_t\xi$ and $c_{t+1} = e_{t+1} + x_{t+1}\xi$. By substituting the constraints, computing the first-order conditions with respect to the objective, and rearranging, the following is obtained:

$$p_t = E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1}\right], \tag{18}$$

which constitutes the core asset pricing equation. Given the payoff x_{t_1} and the investor's consumption choices c_t and c_{t+1}, the market price p_t to anticipate is determined. The equation's economic substance stems from the optimal consumption and portfolio formation's first-order condition. It serves as the foundation for the majority of asset pricing theories.

Moreover, equation (18) can be decomposed using the SDF m_{t+1}:

$$m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)},$$

and subsequently express equation 18 as:

$$\begin{aligned} p_t &= E_t\left[m_{t+1}x_{t+1}\right] \\ p &= E(mx). \end{aligned}$$

The term stochastic discount factor refers to the manner in which m expands upon conventional discount factor concepts. Despite being a generalization, it conveys implication: all risk adjustments can be incorporated by defining a single stochastic discount factor and placing it within the expectation. The uncertainty of m_{t+1} at time t renders it stochastic. The correlation between the random components of the shared discount factor m and the asset-specific payoff x_i produces asset-specific risk adjustments. Most asset pricing models are essentially alternative methods of relating the stochastic discount factor to data.

Additionally, m_{t+1} is frequently referred to as the marginal rate of substitution since it represents the rate at which the investor is willing to save and exchange consumption between time periods. If the equation is expressed as an integral, m_{t+1} is occasionally referred to as the pricing kernel (see, for example, LeRoy et al. (2000)).

In conclusion, asset prices are influenced by expectations concerning future consumption possibilities, which inherently encompass the experience of uncertainty and risk over time, consequently leading to a valuation disparity between specific payoffs and their riskier counterparts.

9.5 Spot price derivation of lower bound

A less condensed version of deriving the lower bound follows than the one found in the text. The price of an n-year dividend future at time t, $P_t^{(n)}$, is the discounted expected dividend n years away:

$$F_t^{(n)} = \frac{\mathbb{E}_t[D_{t+n}]}{1+\theta_t^{(n)}} \tag{19}$$

where D_{t+n} is the expected dividend paid out in n years time and $\theta_t^{(n)}$ is the n-period expected excess return for the on the risk associated with the n-period dividend. The law of one price implies that the price of the underlying stock is interconnected with the price of the dividend future. The value of stock is:

$$S_t = \sum_{n=1}^{\infty} \frac{\mathbb{E}_t[D_{t+n}]}{1+\mu_t^{(n)}}$$

where μ_t^n is the cumulative discount rate connected with the cash flow. For the no-arbitrage condition to hold, it must follow that the sum of an infinite number of (hypothetical) dividend futures discounted by the risk free rate ($y_t^{(n)}$) equals the stock price

$$S_t = \sum_{n=1}^{\infty} \frac{F_t^{(n)}}{1+y_t^{(n)}}$$

as $(1+\theta_t^{(n)})(1+y_t^{(n)}) = 1+\mu_t^{(n)}$. The interconnectedness between the price of dividend futures and stock prices is what give us the opportunity to break down the market's expectation of dividend growth by maturity. I will, with very simple assumptions, derive a lower bound growth expectation for dividends using dividend future prices.

I can rewrite (19) to

$$F_t^{(n)} = D_t \frac{[D_{t+n}/D_t]}{1+\theta_t^{(n)}} = D_t \frac{G_t^{(n)}}{1+\theta_t^{(n)}}$$

where I define the expected dividend growth to be $G_t^{(n)} = [D_{t+n}/D_t]$. Looking the change in expected dividend growth over a short time horizon from t to t', such that I can assume that $D_t \approx D_{t'}$ I get

$$\Delta F_{t'}^{(n)} = \frac{\Delta G_{t'}^{(n)}}{\Delta \Theta_{t'}^{(n)}}.$$

where $\Theta_t^{(n)} = 1+\theta_t^{(n)}$, $\Delta F_{t'}^{(n)} = F_{t'}^{(n)}/F_t^{(n)}$, $\Delta G_{t'}^{(n)} = G_{t'}^{(n)}/G_t^{(n)}$ and $\Delta\Theta_{t'}^{(n)} = \Theta_{t'}^{(n)}/\Theta_t^{(n)}$

By assuming that the expected excess return does not decrease between time t and t', that is $\Delta\Theta_{t'}^{(n)} \geq 1$, I can achieve a lower bound on dividend growth expectations

$$\Delta G_{t'}^{(n)} - 1 \geq \Delta F_{t'}^{(n)} - 1.$$

Since the expected excess return is associated with investor's risk aversion and the perception of uncertainty surrounding the dividend, I believe the above assumption is reasonable when modelling investors response to external shocks such as the outbreak of a war or a pandemic.

9.6 Data

Index Returns and Dividends: In this study, information on index returns, encompassing both gross and price indices, as well as dividend futures prices for all the markets under examination, was obtained from Refinitiv Eikon. However, it should be noted that the data pertaining to the SP 500 dividend futures exhibited some discrepancies, as several contracts were missing. Despite assistance from the Refinitiv Eikon support team, it proved difficult to create a coherent chain of futures for this particular index.

Gross Domestic Product: To accurately represent the economic performance of the markets examined in this study, GDP data was gathered from each market's respective national database, reflecting the seasonally adjusted real GDP. In the context of the European Union, the analysis utilized the seasonally adjusted GDP for the 27 EU member countries, in addition to the United Kingdom. This approach allows for a comprehensive understanding of the economic dynamics at play within the studied regions.

Prices: As the price of the derivatives I used the settlement price, which is the volume-weighted average price during the day, as provided by Refinitv Eikon.

Lastly, I would like to provide some general comments about the data that may be useful for readers. While working with the data, I have encountered numerous discrepancies, primarily regarding available bids and asks (see, for example, Figure 15), and even in settlement prices, which are used in the analyses. Another telling example of data peculiarities is Figure 16a. To my mind, there is no apparent reason for the bid and ask quotes to start going haywire in 2021, one year after being perfectly aligned under heavy turbulence. To my understanding, some of the data appears to be incorrect. I have dedicated considerable time to discussing this issue with Refinitiv Eikon's support, providing them with multiple materials for investigation. However, during the three months of communication, they have been unable to confirm any inaccuracies in their data. Considering their expertise and access to better analytical tools, I have decided not to alter the original data and to present it as is.

10 Appendix B: Tables and Figures

10.1 Introduction

Table 7: Listed dividend futures on indices

Index	Bloomberg code	Dividend future prefix	Dividend index
Eurostoxx50	SX5E	DED	SX5ED
FTSE	UKX	UKD	F1DV
Nikkei225 (SGX)	NKY	MND	NKYDIV
Nikkei225 (TSE)	NKY	INT	NKYDIV
TOPIX	TPX	TDI	TPXDIV
TOPIX Core 30	TPXC30	TCD	TPXC30D
SMI	SMI	SMD	SMIDP
CAC	CAC	XFD	CACDI
DAX	DAXK	DKR	DXDIVPT
DivDax	DIVDAX	DVD	DDXDIVPT
Select Dividend 30	SD3E	DSD	SD3ED

Note: All of the listed dividend futures have different characteristics,maturities and underlying qualities. There may also exist other contractsas I perhaps did not capture all available listings. Please refer to the relevant exchange for the latest and most comprehensive information on dividend futures trading.

10.2 Dividend Futures

Table 8: Correlation Between ITA and GER Term Structures

(a) FTSE MIB.

	C 1	C 2	C 3	C 4
NS 1	1.00	0.99	0.93	0.87
NS 2	1.00	0.99	0.90	0.81
NS 3	0.99	0.98	0.91	0.86
NS 4	0.94	0.93	0.89	0.91

(b) DAX

	C 1	C 2	C 3	C 4	C 5
NS 1	0.97	0.91	0.87	0.86	0.86
NS 2	0.97	0.96	0.93	0.92	0.92
NS 3	0.96	0.97	0.95	0.95	0.95
NS 4	0.96	0.97	0.97	0.96	0.96
NS 5	0.96	0.98	0.97	0.97	0.97

Note: This table displays the correlation coefficients for the term structures of the ITA and GER indices. The data is generated from historical market data, with each cell representing the correlation between the respective term structures in the two indices. Higher values (closer to 1) indicate stronger positive correlations, while lower values (closer to 0) indicate weaker correlations. The table provides a comparative overview of the term structure relationships between the two major indices.

Table 9: Correlation Between UK and SWZ Term Structures

(a) FTSE 100.

	C 1	C 2	C 3	C 4	C 5	C 6	C 7
NS 1	0.94	0.89	0.86	0.81	0.79	0.74	0.69
NS 2	0.95	0.95	0.95	0.91	0.87	0.74	0.66
NS 3	0.93	0.96	0.96	0.92	0.88	0.75	0.67
NS 4	0.91	0.95	0.94	0.90	0.87	0.75	0.69
NS 5	0.88	0.92	0.91	0.87	0.84	0.75	0.72
NS 6	0.85	0.88	0.86	0.82	0.81	0.75	0.74
NS 7	0.81	0.83	0.81	0.76	0.77	0.74	0.76

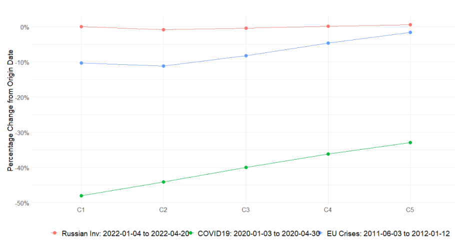
(b) SMI 100.

	C 1	C 2	C 3	C 4	C 5
NS 1	0.98	0.95	0.92	0.92	0.92
NS 2	0.98	0.98	0.97	0.96	0.95
NS 3	0.97	0.98	0.98	0.97	0.96
NS 4	0.97	0.98	0.98	0.97	0.97
NS 5	0.97	0.99	0.98	0.98	0.98

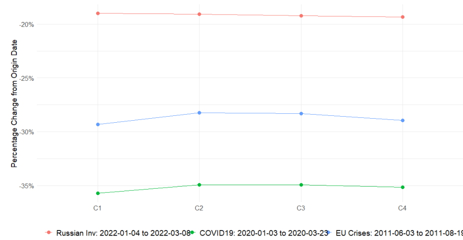
Note: This table displays the correlation coefficients for the term structures of the ITA and GER indices. The data is generated from historical market data, with each cell representing the correlation between the respective term structures in the two indices. Higher values (closer to 1) indicate stronger positive correlations, while lower values (closer to 0) indicate weaker correlations. The table provides a comparative overview of the term structure relationships between the two major indices.

10.3 Changing dividend growth expectations

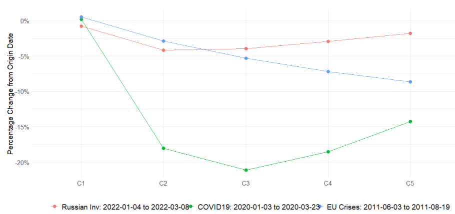
Figure 10: Comparing Percentage Change of the Lower Bound across Three Major Events



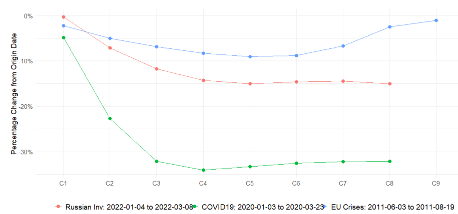
(a) DAX.



(b) FTSE MIB.



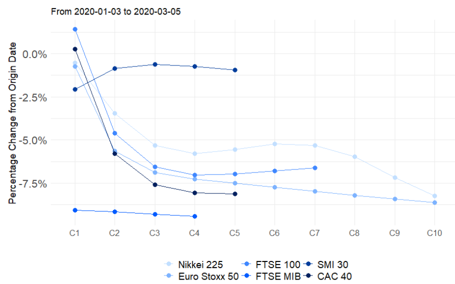
(c) SMI 30.



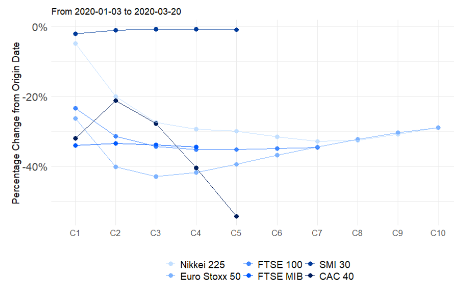
(d) Nikkei Osaka.

Note: The table presents the percentage change in lower bound dividend expectations, calculated from the beginning of the year (January 1st) to the specified dates in the legend. However, for the Eurocrises, the GDP shock is defined from June onwards. The selected date corresponds to a critical period in the Eurocrises, marked by events such as Portugal's impending default, the approval of the second rescue package for Greece, and the introduction of new European austerity measures. Note that the dates for DAX have been changed to accommodate missing transactions.

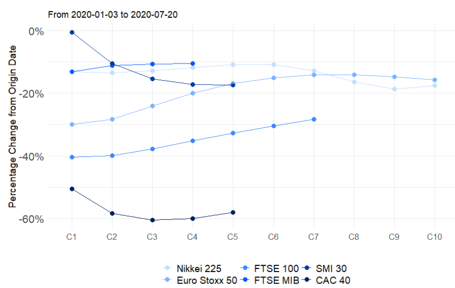
Figure 11: Lower Bound Change in Expected Dividend Growth During the COVID-19 Pandemic.



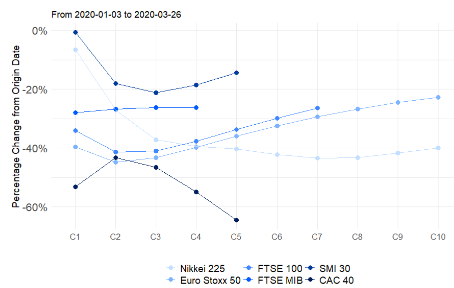
(a) Spread of COVID-19. March 5



(b) Outbreak of the Pandemic. March 20



(c) Stimulus. March 26



(d) Recovery. July 20

Note: This figure illustrates the lower bound development during the COVID-19 pandemic, following the style and dates of Gormsen and Koijen (2020), while incorporating additional markets from this study. It reveals a similar trend, with both the SMI 30 and CAC 40 experiencing minimal trades, reflecting their restricted movement during this period despite existing market prices. For the C2 contract, the SMI exhibited an approximate 10% spread on days when quotes were available. The figure also presents the relative price of dividend futures with varying maturities, displaying the percentage change in prices since January 1st. Dividend futures represent claims on the dividends paid on an index in a specified year.

Table 10: Detailed Showcase of Changes In the Cubic Spline Model During Russias Invasion of Ukraine

	2022-03-10						2022-03-20				
Contract	Nikkei 225	Euro Stoxx 50	FTSE 100	FTSE MIB	SMI 30	Contract	Nikkei 225	Euro Stoxx 50	FTSE 100	FTSE MIB	SMI 30
C1	-0.012	-0.012	-0.043	-0.118	-0.019	C1	-0.007	-0.002	-0.030	-0.085	-0.012
C2	-0.077	-0.066	-0.072	-0.120	-0.032	C2	-0.069	-0.036	-0.046	-0.076	-0.019
C3	-0.114	-0.117	-0.090	-0.122	-0.034	C3	-0.108	-0.067	-0.054	-0.073	-0.006
C4	-0.124	-0.143	-0.097	-0.124	-0.029	C4	-0.122	-0.081	-0.056	-0.071	0.009
C5	-0.116	-0.145	-0.098		-0.023	C5	-0.113	-0.079	-0.056		0.019
C6	-0.102	-0.137	-0.098			C6	-0.092	-0.072	-0.054		
C7	-0.100	-0.127	-0.099			C7	-0.085	-0.064	-0.052		
C8	-0.112	-0.118				C8	-0.094	-0.059			
C9	-0.122	-0.112				C9	-0.105	-0.055			
C10	-0.128	-0.107				C10	-0.111	-0.052			

Note: This table displays the percentage point change in lower-bound dividend growth expectations subsequent to Russia's invasion of Ukraine, expressed as decimals (e.g., 0.026 represents a 2.6% change). The dates presented at the top of the table indicate a cutoff from the reference date of February 24th.

10.4 Expected Dividend Growth

Table 11: 2022 Changing Lower Bound Dividend Expectation

		Estimate								
Market	Date	C1	C2	C3	C4	C5	C6	C7	C8	C9
EU	2022-04-06	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01
	2022-05-03	-0.00	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01	-0.01
ITA	2022-04-06	-0.11	-0.10	-0.10	-0.09	NA	NA	NA	NA	NA
	2022-05-03	-0.11	-0.09	-0.09	-0.09	NA	NA	NA	NA	NA
FRA	2022-04-06	2.60	0.02	0.13	-0.33	1.28	NA	NA	NA	NA
	2022-05-03	2.63	0.02	0.14	-0.33	1.30	NA	NA	NA	NA
UK	2022-04-06	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	NA	NA
	2022-05-03	-0.00	0.01	0.01	0.01	0.01	0.00	0.00	NA	NA
JAP	2022-04-06	0.08	-0.01	-0.03	-0.03	-0.02	-0.02	-0.06	-0.03	-0.03
	2022-05-03	0.07	-0.02	-0.03	-0.03	-0.02	-0.02	-0.06	-0.03	-0.03
SMI	2022-04-06	-0.00	-0.00	0.00	0.01	0.01	NA	NA	NA	NA
	2022-05-03	-0.00	0.00	0.00	0.01	0.01	NA	NA	NA	NA
DE	2022-04-06	0.00	0.00	0.00	0.00	0.00	NA	NA	NA	NA
	2022-05-03	0.00	0.00	0.00	0.00	0.00	NA	NA	NA	NA

Table 12: 2022 Changing Lower Bound GDP Expectations

		Estimate									
Country	Date	C1_GDP	C2_GDP	C3_GDP	C4_GDP	C5_GDP	C6_GDP	C7_GDP	C8_GDP	C9_GDP	C10_GDP
EU	2022-04-06	-0.005	-0.008	-0.013	-0.017	-0.019	-0.018	-0.016	-0.012	-0.007	-0.001
	2022-05-03	-0.004	-0.005	-0.009	-0.012	-0.014	-0.014	-0.012	-0.009	-0.005	0.001
ITA	2022-04-06	-0.035	-0.029	-0.029	-0.028	NA	NA	NA	NA	NA	NA
	2022-05-03	-0.034	-0.028	-0.028	-0.027	NA	NA	NA	NA	NA	NA
FRA	2022-04-06	1.687	0.011	0.085	-0.216	0.830	NA	NA	NA	NA	NA
	2022-05-03	1.705	0.013	0.088	-0.214	0.840	NA	NA	NA	NA	NA
UK	2022-04-06	-0.005	-0.003	-0.001	-0.001	-0.001	-0.002	-0.002	NA	NA	NA
	2022-05-03	-0.000	0.003	0.005	0.004	0.003	0.002	0.001	NA	NA	NA
JAP	2022-04-06	0.057	-0.010	-0.020	-0.021	-0.016	-0.013	-0.045	-0.022	-0.022	-0.022
	2022-05-03	0.056	-0.011	-0.021	-0.023	-0.015	-0.012	-0.044	-0.021	-0.021	-0.021
SMI	2022-04-06	-0.001	-0.001	0.000	0.002	0.002	NA	NA	NA	NA	NA
	2022-05-03	-0.001	0.000	0.001	0.002	0.002	NA	NA	NA	NA	NA
DE	2022-04-06	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA
	2022-05-03	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	NA

Table 13: 2020 Changing Lower Bound Dividend Expectation

		Estimate								
Market	Date	C1	C2	C3	C4	C5	C6	C7	C8	C9
EU	2020-04-06	-0.1689	-0.1533	-0.1348	-0.1189	-0.1069	-0.0992	-0.0951	-0.0939	-0.0948
	2020-05-04	-0.1256	-0.1216	-0.1097	-0.0980	-0.0888	-0.0828	-0.0795	-0.0786	-0.0795
	2020-06-04	-0.0966	-0.0900	-0.0761	-0.0635	-0.0547	-0.0501	-0.0490	-0.0507	-0.0545
ITA	2020-04-06	-0.3894	-0.3710	-0.3685	-0.3674	NA	NA	NA	NA	NA
	2020-05-04	-0.3930	-0.3761	-0.3781	-0.3771	NA	NA	NA	NA	NA
	2020-06-04	-0.2363	-0.2156	-0.2143	-0.2142	NA	NA	NA	NA	NA
FRA	2020-04-06	-0.2870	-0.2654	-0.2172	-0.3884	-0.3744	NA	NA	NA	NA
	2020-05-04	-0.2620	-0.2409	-0.1918	-0.3547	-0.2107	NA	NA	NA	NA
	2020-06-04	-0.2418	-0.2211	-0.1714	-0.3464	-0.1888	NA	NA	NA	NA
UK	2020-04-06	-0.2324	-0.2205	-0.1963	-0.1735	-0.1356	-0.1551	-0.1405	NA	NA
	2020-05-04	-0.1898	-0.2078	-0.1668	-0.1478	-0.1241	-0.1385	-0.1295	NA	NA
	2020-06-04	-0.1589	-0.1783	-0.1328	-0.1150	-0.0899	-0.1074	-0.0942	NA	NA
JAP	2020-04-06	-0.1405	-0.1456	-0.1444	-0.1434	-0.1439	-0.1462	-0.1500	-0.1549	-0.1605
	2020-05-04	-0.0859	-0.0907	-0.0878	-0.0835	-0.0797	-0.0765	-0.0739	-0.0719	-0.0703
	2020-06-04	-0.0518	-0.0596	-0.0587	-0.0561	-0.0536	-0.0517	-0.0502	-0.0491	-0.0483
SMI	2020-04-06	0.0000	-0.0798	-0.0541	-0.0487	-0.0340	NA	NA	NA	NA
	2020-05-04	0.0000	-0.0798	-0.0541	-0.0487	-0.0340	NA	NA	NA	NA
	2020-06-04	0.0000	-0.0736	-0.0541	-0.0487	-0.0340	NA	NA	NA	NA
DE	2020-04-06	-0.1763	-0.1769	-0.1136	-0.1136	-0.1136	NA	NA	NA	NA
	2020-05-04	-0.1763	-0.1769	-0.1136	-0.1136	-0.1136	NA	NA	NA	NA
	2020-06-04	-0.1763	-0.1769	-0.1136	-0.1136	-0.1136	NA	NA	NA	NA

Table 14: Pooled Regressions of Dividend Growth on Dividend Yields and Country Dummies

	Model e_1		Model e_2	
Parameter	Estimate	(HAC_SE)	Estimate	(HAC_SE)
Intercept	0.0023	(0.0001)	0.0026	(0.0002)
e_1	0.4698	(0.0021)		
e_2			0.9921	(0.0012)
France	0.0033	(0.0008)	0.0005	(0.0002)
UnitedKingdom	0.0042	(0.0004)	0.0022	(0.0003)
Japan	0.0186	(0.0006)	0.0141	(0.0004)
Switzerland	0.0065	(0.0004)	0.0035	(0.0003)
Germany	0.0016	(0.0002)	-0.0009	(0.0002)
Observations	18735		18735	

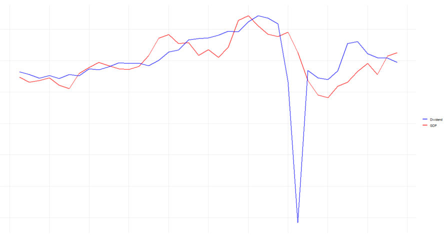
Note: This table presents the pooled regression results for e_1 and e_2. While the estimates are statistically significant, the coefficient for e_2 appears to be unusually high compared to both country-specific and aggregated results, as well as the findings reported by Gormsen and Koijen (2020). It is worth noting that Gormsen and Koijen (2020) do not provide results for timeframes other than the second, limiting the scope for comparison across longer time horizons. Additionally, the use of daily data in this analysis, as opposed to the quarterly data employed by Gormsen and Koijen (2020), may introduce differences in the results and potentially obscure some underlying patterns.

Table 15: 2011 Changing Lower Bound Dividend Expectation

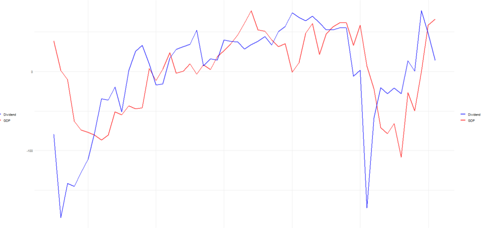
		Estimate									
Market	Date	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
EU	2011-06-06	0.00128	0.00160	0.00013	-0.00201	-0.00425	-0.00634	-0.00819	-0.00979	-0.01114	-0.01229
	2011-07-20	0.00262	-0.00193	-0.00670	-0.01107	-0.01486	-0.01804	-0.02068	-0.02286	-0.02466	-0.02614
ITA	2011-06-06	-0.07159	-0.07143	-0.10360	-0.05249	NA	NA	NA	NA	NA	NA
	2011-07-20	-0.18081	-0.18528	-0.22020	-0.24547	NA	NA	NA	NA	NA	NA
FRA	2011-06-06	-0.00260	0.00756	0.00648	0.00534	0.00270	NA	NA	NA	NA	NA
	2011-07-20	-0.00104	-0.00076	-0.00233	-0.00507	-0.01052	NA	NA	NA	NA	NA
UK	2011-06-06	0.00241	-0.00019	0.00038	-0.00392	-0.00408	-0.00575	-0.00820	NA	NA	NA
	2011-07-20	0.00301	-0.00426	-0.00567	-0.01082	-0.01113	-0.01436	-0.01793	NA	NA	NA
JAP	2011-06-06	0.02174	0.01916	0.01194	0.00608	0.00475	0.00223	0.00272	0.00025	-0.00296	-0.01519
	2011-07-20	0.04025	0.04975	0.04203	0.03266	0.02922	0.02456	0.02175	0.01980	0.01456	0.00169
SMI	2011-06-06	-0.00016	0.00225	0.00194	0.00147	-0.00098	NA	NA	NA	NA	NA
	2011-07-20	-0.00236	-0.00434	-0.00581	-0.00928	-0.01061	NA	NA	NA	NA	NA

10.5 Estimating Lower Bound Implied GDP Growth

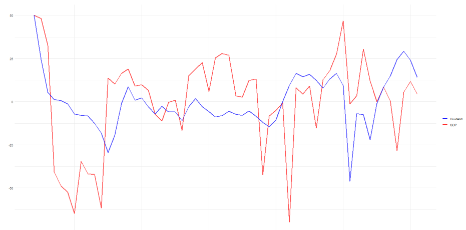
Figure 12: The Cyclical Part of Dividends and GDP for a Sample of Countries.



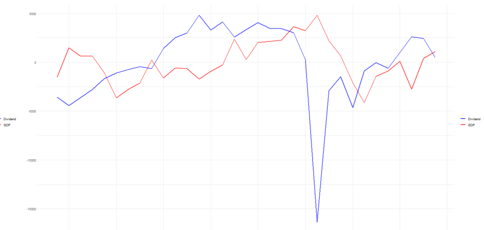
(a) France GDP and Dividends.



(b) Japan GDP and Dividends.



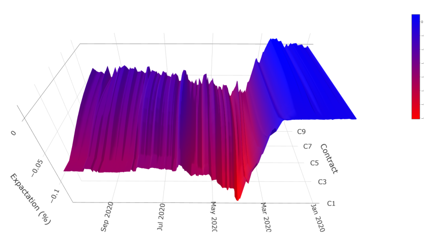
(c) Switzerland GDP and Dividends.



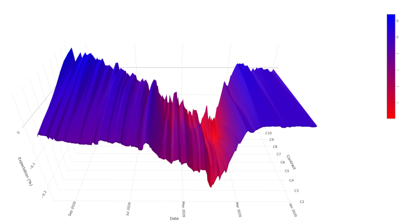
(d) United Kingdom GDP and Dividends.

Note: The present visual representation depicts two series that showcase the cyclical components of dividends and GDP, respectively. The application of the Hamilton-filter has been employed to extract the aforementioned cyclical parts from the original data. In this context, the normalization of the axis in the visual representation may lead to a reduced degree of interpretive significance compared to traditional charts. One could argue that the axis is redundant and could be omitted from the visualization without sacrificing the content. The fundamental objective of the aforementioned visual representation is to illustrate the correlation between the cyclical component of dividends and that of GDP in a graphical manner.

Figure 13: 2020 Euro Stoxx 50 GDP Expectations Comparison



(a) 5.2 Method.



(b) 5.3 Method.

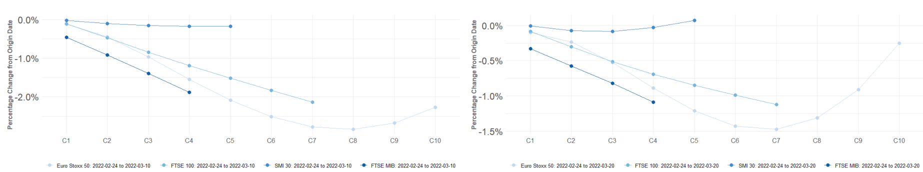
Note: The presented figures depict the temporal evolution of economic variables following the outbreak of the COVID-19 crisis. The methods employed in the analysis include the two techniques discussed in Sections (5.3) and (5.2). The figures demonstrate that there are subtle differences in the expected changes in surface levels between the two methods. These differences may reflect variations in the underlying assumptions and modeling frameworks.

Table 16: Relationship Between Cyclical GDP and Dividends

	Eurozone		France		United Kingdom		Japan	
Correlation	0.0781	0.0781	0.3567	0.3567	0.6906	0.6906	0.5126	0.5126
Eigenvalues	0.2871	0.1247	0.4458	0.1103	0.3590	0.1413	0.3112	0.0693
Test Statistic	7.4573	18.9540	4.3248	21.8353	8.5323	24.9069	3.9503	20.5029
10pct Confidence	6.5000	12.9100	6.5000	12.9100	6.5000	12.9100	6.5000	12.9100
5pct Confidence	8.1800	14.9000	8.1800	14.9000	8.1800	14.9000	8.1800	14.9000
1pct Confidence	11.6500	19.1900	11.6500	19.1900	11.6500	19.1900	11.6500	19.1900
Eigenvectors Dividends L2	1.0000	-57.7274	1.0000	-565.2655	1.0000	-4.2775	1.0000	-17.4372
Eigenvectors GDP L2	1.0000	2198.0890	1.0000	230.9683	1.0000	-0.1816	1.0000	-2.8854
Weights Dividends	-0.2465	-0.0007	-0.2786	0.0009	-0.2499	0.0017	-0.1236	0.0201
Weights GDP	0.0047	-0.0001	-0.0726	-0.0006	-0.1024	-0.1074	-0.1957	-0.0075
	United States		Italy		Switzerland		Germany	
Correlation	0.6589	0.6589	0.1198	0.1198	0.2697	0.2697	-0.1804	-0.1804
Eigenvalues	0.3127	0.0833	0.3947	0.1649	0.2144	0.1640	0.3295	0.1935
Test Statistic	4.8715	21.0026	6.8455	19.0749	10.0344	13.5131	6.6674	12.3894
10pct Confidence	6.5000	12.9100	6.5000	12.9100	6.5000	12.9100	6.5000	12.9100
5pct Confidence	8.1800	14.9000	8.1800	14.9000	8.1800	14.9000	8.1800	14.9000
1pct Confidence	11.6500	19.1900	11.6500	19.1900	11.6500	19.1900	11.6500	19.1900
Eigenvectors Dividends L2	1.0000	-0.6523	1.0000	-3676.7198	1.0000	6.0336	1.0000	-1122.2776
Eigenvectors GDP L2	1.0000	0.6282	1.0000	1757.4841	1.0000	-4.1730	1.0000	165.7340
Weights Dividends	-0.3764	0.1647	-0.3244	0.0000	-0.1879	-0.0399	-0.1426	0.0003
Weights GDP	-0.0213	-0.1752	-0.0720	-0.0001	-0.2727	0.0363	-0.1244	-0.0010

Note: This table presents the relationship between cyclical GDP and dividends for eight countries/regions. The analysis was performed using a cointegration analysis with the Johansen test, and the table reports the correlation coefficients, eigenvalues, test statistics, critical values at 10%, 5 %, and 1% significance levels, eigenvectors for dividends and GDP at lag 2, and the weights for dividends and GDP. The cointegration analysis was conducted on the input data frames for each country/region, which contained two columns: the cyclical components of GDP and dividends. The correlation coefficients indicate the strength and direction of the linear relationship between these two variables. The eigenvalues, test statistics, and critical values at different significance levels are used to determine the presence of cointegrating relationships between the variables. The eigenvectors at lag 2, which is also the number of lags the model is estimated with, and the weights for dividends and GDP provide additional information about the nature of the cointegration relationships.

Figure 14: European GDP Expectations 2022



(a) 2022-02-24 - 2022-03-10 (b) 2022-02-24 - 2022-03-10

Note: The corresponding GDP expectations derived for the same dates as the figure 2.

10.6 The dividend futures market, liquidity and idiosyncrasies

Table 17: Euro Stoxx 50 C1 Contract Summary Statistics

Year	Open Interest	Mean Volume	Bid-Ask Spread
2008	4,554.15	87.26	
2009	62,054.15	1,392.57	
2010	115,991.55	886.66	
2011	143,631.63	1,656.63	0.13
2012	155,364.57	2,517.48	0.12
2013	172,546.56	1,603.80	0.08
2014	158,293.69	2,607.43	0.09
2015	194,760.90	2,665.50	0.11
2016	226,936.42	3,867.25	0.07
2017	202,566.24	2,854.87	0.06
2018	236,904.39	3,042.88	0.06
2019	229,734.33	3,025.52	0.06
2020	221,319.29	5,385.75	0.19
2021	85,985.98	1,707.92	49.97
2022	102,161.54	1,765.83	11.19

Note: Open Interest and Volume corresponds to the daily average over the specified year.

Table 18: FTSE 100 C1 Contract Summary Statistics

Year	Open Interest	Volume	Bid-Ask Spread
2009	17,261	37	–
2010	114,956	133	–
2011	95,111	186	0.88
2012	102,018	287	0.64
2013	107,162	510	–
2014	129,951	275	–
2015	83,653	216	–
2016	70,985	203	–
2017	66,757	246	0.92
2018	40,910	219	1.14
2019	62,175	625	1.37
2020	78,811	1,185	3.65
2021	102,144	1,994	1.07
2022	82,914	1,687	1.39

Note: Open Interest and Volume corresponds to the daily average over the specified year.

Table 19: CAC 40 C1 Contract Summary Statistics

Year	Open Interest	Volume	Bid-Ask Spread
2009	85.86	50.50	3.96
2010	10,777.47	718.56	1.50
2011	17,157.50	100.00	2.38
2012	12,219.95	560.00	3.27
2013	6,282.13	1,000.00	2.66
2014	29,876.33	5,453.75	1.40
2015	28,044.39	764.17	2.20
2016	20,694.83	1,133.33	1.52
2017	52,731.35	3,307.81	0.74
2018	68,670.31	2,055.88	0.51
2019	50,995.23	1,367.00	0.44
2020	39,371.76	1,468.18	
2021	26,108.74	237.50	
2022	36,023.67	150.00	

Note: Open Interest and Volume corresponds to the daily average over the specified year.

Table 20: FTSE MIB C1 Contract Summary Statistics

Year	Open Interest	Volume	Bid-Ask Spread
2004	7,041.80	4,208.11	135.69
2005	21,307.95	12,730.27	6.10
2006	23,690.62	14,479.02	6.71
2007	23,653.90	17,067.55	7.43
2008	33,509.38	17,707.79	12.32
2009	30,092.08	15,160.36	13.76
2010	39,585.04	19,224.27	37.82
2011	44,122.42	22,001.96	239.80
2012	34,977.34	21,506.07	240.56
2013	44,101.41	23,642.06	11.96
2014	48,837.77	30,976.24	11.70
2015	56,206.70	34,647.26	8.62
2016	50,740.20	38,299.71	10.66
2017	34,170.96	25,087.69	6.52
2018	66,014.87	29,588.48	4.03
2019	112,025.68	23,204.73	2.71
2020	137,361.45	37,672.03	16.37
2021			
2022			
2023			

Note: Open Interest and Volume corresponds to the daily average over the specified year.

Table 21: Nikkei 225 C1 Contract Summary Statistics

Year	Open Interest	Volume	Bid-Ask Spread
2010	327.44	13.52	1.09
2011	3,698.05	44.86	
2012	8,426.92	81.52	
2013	17,028.45	45.27	1.12
2014	17,466.84	74.88	0.55
2015	13,451.43	35.12	2.40
2016	13,847.40	52.02	1.26
2017	14,116.18	80.23	0.80
2018	9,523.93	29.46	1.05
2019	10,356.84	49.69	1.43
2020	8,704.65	53.96	3.39
2021	5,999.03	9.26	1.80
2022	3,529.65	17.61	3.99

Note: Open Interest and Volume corresponds to the daily average over the specified year.

Table 23: Summary of Trading Characteristics for Ten Futures Contracts During 2020 - 2022

	EU			France			Japan		
Contract	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)
C1	3183.75	136490.64	54.37	768.75	33803.01	-	34.13	6077.82	1.37
C2	5913.43	152134.80	11.51	1430.19	40585.09	-	44.18	4717.35	1.19
C3	5963.80	141254.87	44.74	112-	36730.90	-	23.67	1769.39	1.13
C4	5126.64	97853.10	12.70	1860.50	24931.64	-	10.71	640.97	2.31
C5	4390.69	134441.61	0.78	1083.85	31260.46	-	4.82	38.09	3.37
C6	2466.00	89829.61	1.12	-	-	-	1.00	4.95	11.17
C7	1080.34	46585.82	2.09	-	-	-	-	0.74	10.63
C8	719.79	32544.25	4.14	-	-	-	-	-	10.01
C9	277.55	17033.14	8.95	-	-	-	-	-	-
C10	217.23	13051.17	13.58	-	-	-	-	-	-
	Italy			Switzerland			UK		
Contract	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)	Volume	Open Interest	Bid Ask Spread (%)
C1	37672.03	137496.14	0.20	23074.97	22.06	410.86	1602.97	87931.61	1.86
C2	2350.30	7319.03	0.52	22845.49	41.17	322.37	1628.98	78663.47	3.91
C3	10.85	44.12	1.09	22630.55	32.91	272.68	1331.89	55746.30	2.74
C4	-	-	-	22455.08	38.28	117.40	1197.92	35853.70	2.69
C5	-	-	-	-	21.73	28.19	96.97	331.14	4.43
C6	-	-	-	-	-	-	834.89	15891.68	4.44
C7	-	-	-	-	-	-	427.20	5848.34	3.90
C8	-	-	-	-	-	-	-	-	-
C9	-	-	-	-	-	-	-	-	-
C10	-	-	-	-	-	-	-	-	-

Note: The table presents averages across the entire sample period. For instance, Open Interest signifies the average daily amount of outstanding contracts. Volume refers to the daily average of traded contracts, while bid-ask spread represents the average daily percentage discrepancy between buying and selling prices in the market.

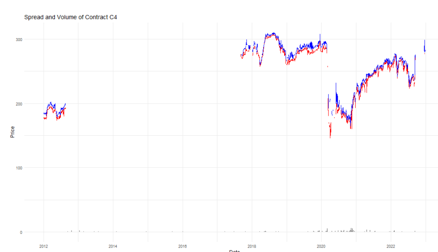
Table 22: SMI 30 C1 Contract Summary Statistics

Year	Open Interest	Volume	Bid-Ask Spread
2009	90.06	0.00	–
2010	1,631.48	11.28	–
2011	2,200.55	18.97	–
2012	2,192.44	65.15	–
2013	2,293.39	66.61	0.43
2014	1,570.92	14.14	0.65
2015	1,340.65	46.23	1.26
2016	730.84	28.33	2.17
2017	427.00	65.00	3.72
2018	328.62	29.50	2.07
2019	459.67	28.75	2.47
2020	343.03	18.33	4.88
2021	224.95	10.00	2.50
2022	665.58	23.85	3.18

Note: Open Interest and Volume corresponds to the daily average over the specified year.

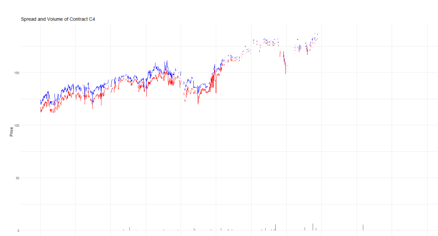
Figure 15: Spread and Volume Across Various Contracts with Missing Data

(a) FTSE 100 C2.



(b) FTSE 100 C4.

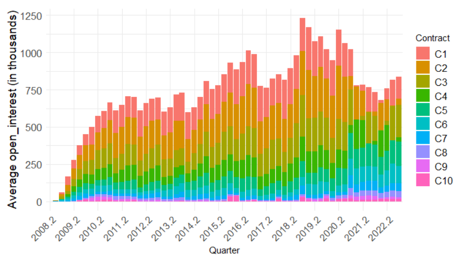
(c) CAC 40 C2.



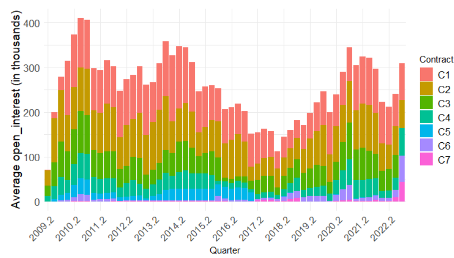
(d) CAC 40 C4.

Note: This image illustrates the inadequate data quality obtained from Refinitiv Eikon. It is evident that volume data and the bid-ask spread are missing for various time periods. Despite extensive communication and a considerable amount of time spent discussing the issue, over two months, with Refinitiv Eikon, they were unable to provide a solution or confirm whether my assertion of missing data was accurate.

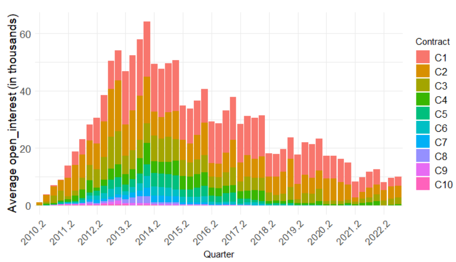
Figure 16: Average On Exchange Open Interest per Market



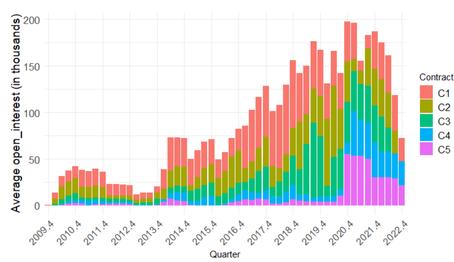
(a) Euro Stoxx 50



(b) FTSE 100



(c) Nikkei 225



(d) CAC 40

Note: The bar chart represents the average open interest (in thousands) of contracts C1 through C10 for each quarter across the entire sample period. The open interest for each contract is stacked, meaning the total height of each bar represents the combined average open interest for all contracts in that quarter. The colors differentiate each contract, with C10 at the bottom and C1 at the top of each bar. Note that the data for each contract is averaged over the sample period, providing a summary view of contract volumes over time.