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Return predictability with the dividend yield: an international and cross-sectional examination in the context of the business cycle

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ABSTRACT

In this paper, return predictability using the dividend yield is studied under the context of the business cycle. Ordinary Least Squares regressions are run on three countries and four equity cross-sections for the period June 1995 to September 2022. The results show that periods of recessions do not moderate the effect of the dividend yield in predicting return. The paper additionally uses Multilevel Logit regressions run on 102 equity indexes across 32 countries for the period March 2007 to May 2022. The results show a positive relationship between proportion of recessionary periods and the probability an index sees it return being predictable by the dividend yield. Combinedly, the findings show that the dividend yield is able to track variation in return better during times of economic contraction, but its forecasting effect is not altered when in such periods.

Keywords: return predictability, dividend yield, business cycle

JEL codes: E32, G12, G17

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CHAPTER 1 Introduction

Moving on from what is now coined the "Great Lockdown", society sees itself recovering from the devastating COVID-19 pandemic that had once ravaged the world, both in terms of human capital as well as economic activity. With government restrictions keeping businesses shut and trade suspended, the global economy saw itself heading into the "deepest recession since the Second World War" (World Bank Group, 2022). Interestingly however, a survey has shown that 15% of US stock market participants started their journey in 2020 amidst the pandemic (Schwab, 2021), demonstrating a compelling avenue where interest in investing still fares well with times of turmoil. This rise in popularity does not seem to be a one-off instance also, but part of an increasing trend – it is approximated that 61% of Americans own equity investments in 2023, an increase from 58% in 2022 and 56% in 2021 (Gallup, 2024) while institutional investors may see a rise in equity allocations to take advantage of opportunities from changing global dynamics (Schroders, 2023). With such increase in trading activity, the age-old subject of return modelling, to investigate the components that drive the return observed on the market and use it in our own forecasts, is becoming ever more significant to study upon, both economically and socially.

Given its gravity, the exercise of modelling return has captured the minds of academia with the vast literature produced. Especially, the model of Campbell and Shiller (1988) where the logarithm dividend-price ratio (DP) relates to all future one-period discount rates and dividend growth rates (DG) has inspired numerous papers documenting the use of DP to predict return. Chen (2009) conducts an analysis using a sample spanning between 1872 to 2005 of the United States (US) stock market, observing predictability for return and not DG, a pattern considered a stylized fact, in the post-war (post-1954) period. Interestingly, the trend is reversed in the pre-war period (pre-1926). Cornell (2014) also reports patterns dissimilar to conventional wisdom in other countries such as France, Germany, Italy, while Maio and Santa-Clara (2015) reports such conflicting trends for portfolios of small and value stocks. All these literatures combinedly depict a certain degree of heterogeneity in return predictability when using DP. On the other hand, the impact of the business cycle on return predictability has also garnered the attention of researchers. Golez and Koudijs (2018) performed analysis on different equity markets of the last four centuries from 1629 to 2015. Part of their research made use of a dummy variable indicating recessions and using it in a regression with DP to predict return. The authors report positive coefficients of the dummy and a decrease in the coefficient of DP, indicating higher returns during times of recessions and overarchingly a link between the business cycle and return predictability using DP.

Despite the two areas of literature, no research has explicitly considered how the business cycle impacts the degree in which DP predicts return. Given that one of the channels in which DP predicts return is through the economic cycle as illustrated in Golez and Koudijs (2018), one would expect it to moderate the effect of DP. As such, this paper contributes to existing literature by combining these two realms of literature and examining the direct influence of business cycle on return predictive power of DP. By considering an interaction term between DP and a dummy for recession, the effect is quantified thus allowing interpretations on the magnitude as well as the sign of the impact. The consideration of different countries and equity cross-sections also allows the paper to examine the effect in context of the heterogeneity documented in previous literature. Furthermore, this paper employs a novel methodology in this realm, namely the Multilevel Logit regression, to investigate the systematic impact of the business cycle on return predictability using DP. To the author's knowledge, this is the first paper that aims to address such topic on a general scale. Taken together, the paper provides a comprehensive landscape of return predictability in conjunction with impact of the business cycle, giving valuable insights on the relationship between two areas. Therefore, the research question this paper aims to answer is:

"How does the business cycle affect the efficacy of the dividend yield in predicting return?"

To address the research question, this paper combines the methodology of Chen (2009) and Golez and Koudijs (2018). More specifically, Ordinary Least Squares (OLS) regressions like the two papers will be run for with the dependent variables being return and DG, and with independent variables including DP following the variable construction of Chen (2009). The regressions also include a dummy variable following the Organization of Economic Development recession indicator classifying periods of recessions akin to Golez and Koudijs (2018), as well as an interaction term between the two. The sample period spans from June 1995 to September 2022. Internationally, the countries chosen include the US, the UK, and France with their indicating large-cap indexes S&P500, FTSE100 and CAC40, respectively. Cross-sectionally, the indexes chosen include S&P500 Pure Growth indicating for Large Growth stocks, S&P500 Pure Value for Large Value, S&P600 Pure Growth for Small Growth, and S&P600 Pure Value Small Value. The control variables include the term spread, inflation rates, and oil price uncertainty. Additional robustness tests will be performed with different specifications of the recession indicator.

For the Multilevel (ML) Logit regressions, the data universe contains 102 different indexes of 32 countries across the time period from March 2007 to May 2022. Two dummy variables indicating whether an index sees its return or DG being predictable by DP are constructed by running OLS predictive regressions with return or DG as the outcome variable and DP as the explanatory variable. The dummies will then be fed into the ML Logit regressions with independent variables including the proportion of recessionary periods calculated from the recession indicator, the average inflation rates and the average term spread. These variables are all at the country-level, while on the index-level variables include a dummy indicating whether the index is small-cap or not, and standard deviation of DG in the case of return regressions and vice versa.

The main findings of the paper are as follows. From the OLS analysis, the results report no evidence substantiating for a moderation effect of recessions on DP in predicting returns. The estimated coefficients are mostly insignificant and have conflicting signs depending on the index used. The fit of the models also do not improve when the interaction term is added. On the flip side, analysis with the ML Logit regressions reveal statistically significant effect of recessionary periods on the chance of an index seeing its return predictable by DP. The estimated coefficients are all positive and with significance ranging from 10% to 5%, thus implying that an increase in the proportion of recessionary periods increases the probability of return predictability at the index level.

As for the remainder of the paper, Chapter 2 provides a comprehensive review of the literature related to the subject of predicting return with the dividend yield. The discussion includes the theoretical motivation of the topic, empirical analyses, applicability as well as its relation to the business cycle. Chapter 3 summarizes the data used in the analysis of this paper. The summary includes information such as the sources, details of collection and processing procedure, as well as any additional context relevant for the paper. Chapter 4 outlines the methodology used, where the overarching framework is described in more detail. Afterwards, the construction of the main variables as well as the two techniques used in the paper, namely Ordinary Least Squares and Multilevel Logit regressions, will be discussed. Chapter 5 presents the results of the analysis plus the discussions on model performance and the effects of the independent variables in question in conjunction with the literature discussed. Chapter 6 concludes the findings of the paper as well as presents the limitations and areas of future research for the study.

CHAPTER 2 Theoretical Framework

2.1 Return prediction using dividend yield

The quest to model return has captivated researchers for years. One particular area of literature explores the use of financial ratios in predicting return, using these ratios to measure and track price changes relative to the stock fundamentals (Lewellen, 2004). Within this realm, DP has seen itself receiving the most attention and thorough investigation. The intuition lies in the fact that as a shareholder, one is entitled to receive dividends. Therefore, for the net present value to equal zero, the fair price of a stock must equate the present value of all future dividends. A renowned application of this is the Gordon (1962) growth model, where the price is a function of the dividend, the discount rate and the dividend growth rate. However, the underlying assumption of constant discount and growth rates across the entire investment horizon is considered a major pitfall of this model. The additional constraint of the discount rate required to be larger than the growth rate also pose practical problems.

Another famous literature applying this intuition relating dividends and return is that of Campbell and Shiller (1988). In their seminal work, the authors developed their dividend-ratio model (commonly referred to as the present-value identity) where the logarithm dividend yield is expressed as "an expected discounted value of all future one-period growth-adjusted discount rates" (p. 201). The model can also be interpreted as a dynamic extension of the Gordon (1962) growth model. Utilizing this framework, one can decompose the variation of DP into changing expectations of expected return and of expected cashflows, with the prior having a positive relationship and the latter having a negative relationship. It is these relations that serve as the basis for using the dividend yield to linearly forecast return (detailed inspection of the dividend-ratio model will be discussed in section 4.1).

Given the significant implications of return predictability, numerous empirical investigations have been carried out to assess the model's validity. Fama and French (1988), using a sample of data between 1927 and 1986 of value and equal-weighted portfolios of companies listed on the New York Stock Exchange (NYSE), run predictive regressions of return on DP at different return horizons. They report an increase in predictive power as the horizon length increases, with DP on numerous occasions explaining more than 25% of the variation at the two- to four-year horizon as measured by R-squared. Cochrane (1992) empirically examines the decomposition of variance of the DP following dividend-ratio model. The author's approach involves using an approximation of the present-value identity, algebraic manipulations and taking the expectations to arrive at the final decomposition. Using the same dataset as Fama and French (1988) for the period between 1926 and 1988, the author deduces that changing forecasts of return makes up bulk of the variation in DP. Campbell (1991) employs another technique for the variance decomposition, namely modelling the stock return as an element of a vector autoregression. In doing so, Campbell calculated during the entire sample period between 1927 to 1988, news about cashflows only account for a third of the variation in the DP while the remainder is due to news about return. Given such evidence thus far, it has been widely accepted across academia to be a stylized fact: US stock return is predictable by DP but not DG (applicability of other countries will be discussed in section 2.1.1).

However, there still exists ongoing debates surrounding the validity of the relationship. Goetzmann and Jorion (1993) in their investigation make use of alternative methods such as simulations where return follow the random walk under the null of zero forecastability, as suggested by classical finance theory, as well as bootstrapping, a technique involving take resamples from a sample to perform inferences. In their analysis, the authors report how the empirically observed results lie inside the 95% confidence interval of their simulated distributions, thus providing little statistical substantiation for return predictability using DP. More generally, Welch and Goyal (2007) in their influential paper examine the performance of several prominent return predictors, with DP being amongst them, for the sample period 1926 to 2004. Employing OLS regressions, the authors note two key findings: (1) most predictors do not perform well in-sample, especially between 1975 to 2004, and (2) those that are significant in-sample still fail diagnostic tests following their out-sample performance – consequently raising concerns about return predictability generally and that of DP more specifically.

Nevertheless, approaching the problem from a different angle, Cochrane (2007) in his "defense of return predictability" (p. 1533) argues that evaluation of return predictability must also consider DG predictability, or the lack thereof. Given the present-value identity presumes the variation in DP to contain information on both (expected) return and DG, if return is not forecastable then DG *must* be forecastable. Following this line of reasoning, Cochrane assesses the joint distribution of DP forecasting coefficients on return and DG to test against the null hypothesis of combined absent return predictability and present DG predictability. Conducting analysis on annual data from the Center for Research in Security Prices spanning from 1927 to 2004, Cochrane shows that when considered alone, return predictability offers relatively weak proof. However, when considered in conjunction with DG, it is the lack of DG predictability that provides the bulk of the evidence against the null of no return predictability.

Despite the conflicting evidence, the prospect of return predictability using DP still entails numerous implications across different domains. In macroeconomics, Campbell and Cochrane (1999) employs this relation into their consumption-based model. By modelling stocks as "a claim to the consumption stream" (p. 216) and calibrating it with the DP relationship with return, the authors find their model's predictions accurately depicting the behaviors of the stock market across economic fluctuations throughout a century horizon. When applied to the field of corporate finance, Cochrane (2011) notes how many approaches utilized in accounting and capital structuring implicitly assumes prices only reflect information on cashflows and not discount rates, thus current procedures are no longer sufficient in contexts where the changing components are that of the discount rates. As an illustrative example from Cochrane: when equity and bonds are used to fund a firm, one would use the assets' prices to determine the probability of default. However, if prices change due to discount rates, then this should have no impact on the probability of default. More practically, the use of DP to predict return offers practitioners better informed forecasts, which aids in the performance of their investment strategies – Hull and Qiao (2017) shows a Sharpe ratio when using a market-timing strategy which is four times higher than the typical buy-and-hold strategy, while Abhyankar et al. (2012) shows significantly lower losses of mean-variance portfolios compared to buy-and-hold portfolios during the 2008 global financial crisis.

2.1.1 International heterogeneity

All the literature reviewed thus far documenting return predictability of DP have only pertained to the US for their analysis and although having been acknowledged as a stylized fact, such observations may not materialize in other countries. Cornell (2014) conducts extensive research on 10 countries using a sample period from 1951 to 2012 to compare predictability internationally. Running OLS regressions of return on DP, the author reports trends in return predictability in the US following conventional wisdom, as well as in countries such as the United Kingdom (UK), Japan and Australia. However, some reveal only marginal evidence like France while others such as Canada, Germany, Italy reveal statistically insignificant coefficients of DP in predicting return.

Given the international variation observed, the question of what causes such heterogeneity logically follows. Chen (2009) conducts an analysis to test predictability in the period from 1872 to 2005 and although the data concerns only the US, the extended time series used reveal potential clues hinting at the source of the cross-country variation. Employing monthly predictive regressions with return and DG as dependent variables while DP as the independent variable, Chen finds trends similar to the stylized fact *only* in the post-war (post-1954) period, the trend is reversed in the pre-war (pre-1926) period – that is return is unforecastable by DP, but DG is from 1872 to 1926. Further analysis unveils a difference in volatility of DG and return between two periods, where pre-war period saw more volatile DG compared to return. Chen argues it is this higher variability that allow DP to predict DG and not return in the first seven decades considered. In the post-war period, Chen observes the reverse with higher volatility now in return, thus making return predictable by DP and not DG.

Numerous postulations have been put forth to explain why these differences in volatility exist. Chen et al. (2012) proposes an explanation making use of dividend smoothing, a well-documented phenomenon where firms are reluctant to make changes to their dividend directly following changes in earnings, instead opting to smooth out the dividends (Lintner, 1956). Chen et al. argue that the use of dividend smoothing reduces DG variability, thus making DG predictability difficult and leaving the bulk of DP variation in news about expected return. Alternatively, another argument suggested for reduced DG variability concerns changes in payout policies of firms. Engsted and Pedersen (2010) investigates this argument with their analysis similar to Cornell (2014) on the US, the UK, Sweden and Denmark, finding the typical patterns in the US and the UK but the reversed for the Scandinavian countries. The authors attribute such trends to differences in changes in the share of dividend-paying firms, with the US experiencing a sharp drop from over 80% in the 1950s to just above 20% in 1999 (Fama & French, 2001) while European firms underwent a less substantial decrease, except for the UK (Von Eije and Megginson, 2008). These results altogether present a degree of international heterogeneity in the efficacy of DP in predicting return, thus confining the stylized fact discussed above only to the US and leaving room for further exploration on international applicability.

2.1.2 Equity cross-sections

Another dimension literature often overlooked when investigating return predictability is the cross-sections of the stock market. As Fama and French (1992) have shown in their seminal work, different groups of stocks exhibit different return, notably small-cap and value stocks tend to outperform the market as a whole. This depicts different characteristics among these cross-sections and thus raise the question of generalizability of the stylized fact. Kelly and Pruitt (2013) have noted such heterogeneity and tried to account for it in their analysis. The authors argued that the same set of variables “driving aggregate expectations also govern the dynamics of the entire panel of asset-specific valuation ratios” (p. 1721-1722). Following this reasoning, the authors extracted a unique factor from the different cross-sections split by the book-to-market (BM) ratio, and using a sample ranging from 1930 to 2010, they achieved significant return predictability using this factor as the predictive variable. Furthermore, the results are robust to different degrees of portfolio division and international data.

Nevertheless, the predictive regressions of Kelly and Pruitt (2013) are still performed on the aggregate market portfolio and not the segregated ones. Maio and Santa-Clara (2015) when analyzing predictability on the cross-sections themselves find a substantial degree of heterogeneity between the different groups. The authors sorted their portfolios across two dimensions based on size and BM ratio and using data from 1928 to 2010, they performed predictive regressions similar to literature discussed above using DP as the independent variable. Interestingly, the authors reported trends in accordance with conventional wisdom, that is return predictability, which are only observed in large stocks and more specifically large-growth stocks. On the other hand, DG predictability conversely is only found in portfolios of small stocks, and the evidence is mainly concentrated in small-value stocks.

However, Avramov (2002) reports the opposite observations in terms of cross-sectional predictability. The author makes use of a Bayesian methodology, where different univariate forecasting models, DP being amongst them, are compared and weighted to obtain a combined one. Using this composite model, the author finds evidence of return predictability considerably higher for small value stocks compared to large growth stocks. With the literature aforementioned, it is clear that there exists heterogeneity in return predictability amongst different cross-sections of stocks. Nevertheless, given the apparent contradictions as seen between Maio and Santa-Clara (2015) and Avramov (2002), there is yet to be a clear consensus on what groups of stocks see its return being predictable and hence additional analysis should be conducted to shed light on this puzzle.

2.2 Business cycle in return predictability

The concept of the business cycle, defined as "a repeated series of periods of growth in business activity followed by periods of recession" (Cambridge Dictionary, n.d.), has played a major role in economic history. The world has seen periods of immense growth such as the "Roaring 1920s" where the rising stock market, company expansions and product innovations drove society to economic prosperity, but as well as periods of economic downturn such as the Great Depression or the 2008 global financial crisis, plunging the world into financial turmoil with a bleak outlook on what the future may holds. For these reasons, literature on the subject matter has been continuously produced and applied to different domains, return predictability being no exception.

It has been noted that stock return generally follow a countercyclical pattern with economic conditions (DeStefano, 2004). The simplified intuition follows the inverse relationship between prices and return, with prices usually declining amidst times of difficulty thus raising return. Bolten and Weigand (1998) demonstrate theoretically how stock prices would vary through periods of economic fluctuations due to the interaction between fundamentals of interest rate and corporate earnings under the dividend discount model framework. Upon economic recovery, low interest rates and optimistic earnings expectations drive up the price. As the economy expands, inflationary pressure on interest rates causes firms' cost of capital to rise, a trend that is furthered by tightening monetary policy as the economy further grows. Simultaneously, earnings expectations start to slow as diminishing marginal productivity takes place. This opposite movement between interest rates and earnings cause stock prices to fall, followed by worsening economic outlooks until the economy is in a recession. In this period, stock prices stay low until interest rates are shallow enough and expectations recover to kickstart the cycle again.

Alternative, less "mechanical", justifications for the countercyclicality of return have also been put forth. Campbell and Cochrane (1999), Cochrane (2017) argue that investors during economic downturns become extra risk-averse, leading them to demand higher risk premium. This argument contrasts with traditional macroeconomic reasoning where the investors are thought to respond to changes in wealth, such as changes to expected cashflow or physical capital. On the contrary, Fama and French (1989) argue that it is actually the ability to withstand risk that changes across the business cycle. The authors argue that during recessions, income decreases which lowers the risk-bearing capacity of investors, forcing expected return to be high enough to compel substituting investment for consumption. Their results also note an increasing pattern for the coefficients of DP from high-grade to low-grade bonds, from bonds to stock generally and from big to small stocks, with the authors attributing these observations to the differing risks of the assets that the DP are tracking. More recently, Cujean and Hasler (2017) propose an equilibrium model where the crucial feature lies in how different investors use different forecasting models. This prompts different evaluations of uncertainty which, when the economy experiences a downturn, results in heightened disagreements amongst investors. Such phenomenon causes return to react to past news and ultimately invoking a positive relationship between disagreement and future return.

Bearing in mind the countercyclical nature of return discussed above, what does this entail for its predictability? Golez and Koudijs (2018) performed extensive analysis on three countries with the most important equity markets in different periods within the last four centuries consisting of the Netherlands from 1629 to 1812, the UK from 1629 to 1870, and the US from 1871 to 2015. The authors run predictive regressions of return on DP as with previous literature, however with an addition of a dummy variable indicating whether a particular date was in a recession of not. Results show that the recession dummy exhibit significant and positive coefficients, suggesting return is higher in recessions and in line with the general notion of countercyclicality. Moreover, the coefficient of DP drops after including the recession dummy, illustrating a link between return predictability of DP and the business cycle where economic fluctuations prove to be one of the channels through which DP predicts return.

Henkel et al. (2011) also explores the efficacy of DP, amongst others, in predicting return within the context of the business cycle. The authors perform OLS predictive regressions on the countries belonging to the Group of Seven with sample periods ranging from 36 to 56 years. During periods of expansions, the countries average an adjusted R-squared of 2.88%, with only one country having a barely significant predictive coefficient. Contrastingly, the average adjusted R-squared rises to 15.1% during periods of downturns and four countries out of seven saw a significant coefficient. Furthermore, the authors obtain the adjusted R-squared from the regressions and compare with the cumulative proportion of months which were classified as a recession, resulting in between 70% to 90% correlation, thus illustrating a significant and compelling connection between return predictability and the business cycle with predictability being more prominent in recessions than expansions.

2.3 Hypotheses

Based on the existing literature presented and discussed above, two relevant hypotheses are now formulated for investigation in this paper.

Hypothesis 1: Recessions moderate the dividend yield in predicting return such that the relationship is stronger in times of economic contractions.

Hypothesis 1 is drawn up following the two streams of literature on return predictability with DP and business cycle on return. As noted in section 2.2, return display a countercyclical pattern where a premium is demanded in recessions to compensate for investors' lowered risk-bearing capacity (Fama & French, 1989) or heightened risk-aversion (Campbell & Cochrane, 1999; Cochrane, 2017). Fama and French (1989) also note the variation in return that DP tracks correspond to the risk of the asset in consideration with the increasing pattern of DP coefficients from low- to high-risk assets. With risks rising in times of contraction due to increased default probability and uncertain future outlooks, the coefficient of DP should adjust upwards during such periods to reflect the higher risk associated with the assets. Internationally, this moderation effect should only hold in countries that see return predictability using DP, namely the US and the UK following Cornell (2014), as opposed to France. On the cross-sectional dimension, small-cap indexes should observe more pronounced effects compared to their large-cap counterparts given their higher inherent business risk associated with their small size.

Hypothesis 2: Higher proportion of recessionary periods increase the chance of return being predictable by the dividend yield.

Hypothesis 2 is derived once again from the two streams of literature as in Hypothesis 1. As shown by Golez and Koudijs (2018) and Henkel et al. (2011), predictability of return using DP is more prominent in periods of economic downturns due to the countercyclical nature of return, where "dividend yields predict return because, in part, prices are lower in recessions" (Golez & Koudijs, 2018, p. 260). However, the analysis thus far pertains to only a few indexes and reports on an individual case basis. This hypothesis aims to examine the phenomenon on a wider scale, testing to see if there exists such a systematic positive relationship between the efficacy of DP in predicting return and the proportion of recessionary periods given a fixed time horizon across multiple indexes and different countries. Conceptually, Hypothesis 2 can be regarded as a more general version of Hypothesis 1, where the latter focuses more on the effect of recessions on the intricate details of the DP-return predictive relationship while the former analyzes the broader interaction of the two.

CHAPTER 3 Data

3.1 Index-level data

This paper makes use of equity indexes in its analysis, where the data is sourced from Refinitive Workspace (2024a). For each equity index, monthly data on its price and total return index is retrieved to facilitate the computation of the variables return, DP, and DG following the methodology of Chen (2009) (refer to section 4.2 for details). Given that both the price and total return index are required, equity indexes which only have data for only one of the two, either due to data availability or due to its nature (for example the DAX Performance of Germany is a total return index hence there exists no price index), are discarded. Additionally, the time period considered must also coincide with the other data utilized in the paper, which spreads across different sources and concerns different countries. This restricts the period considered for the OLS regressions from June 1995 to September 2022 for seven indexes extending across three countries and four equity cross-sections. As for the ML Logit regressions, the data universe consists of 102 different equity indexes spread across 32 countries with the time period from March 2007 to May 2022, where details of these indexes and countries can be found in Appendix A.

3.1.1 Time series variables

The first three indexes used in the time series OLS regressions of the paper are: S&P500, FTSE100, CAC40. These are all representative large-cap indexes aim at capturing the benchmark equity worlds of the three countries: the United States (US), the United Kingdom (UK), and France respectively. Motivation for the US follows the stylized fact discussed extensively, allowing for comparisons to be made with the previous literature noting return predictability in the US in the post-war period such as Chen (2009) and Golez and Koudijs (2018). The motivation for the UK and France stems from Cornell (2014) where the UK depicts similar trends to the US while France only exhibits marginal evidence.

The remaining four indexes aim to capture the famous equity cross-sections popularized by Fama & French (1992) and employed for analysis on using DP to predict return in Maio and Santa-Clara (2015): S&P500 Pure Growth for Large Growth stocks, S&P500 Pure Value for Large Value stocks, S&P600 Pure Growth for Small Growth stocks, and S&P600 Pure Value for Small Value stocks. The division across the size dimension makes use of the S&P500 which covers the large-cap range of stocks listed on US stock exchanges while the S&P600 covers the small-cap range. On the value/growth dimension, the “Pure” specification of the indexes ensures there are no overlapping stocks between the two Value and Growth criteria (S&P Dow Jones Indices, 2023), thus preventing any muddling of the characteristic effects.

Panel A	Return				
	Observations	**Mean**	**Std. Dev.**	**Min**	**Max**
US	327	.007	.045	-.184	.121
UK	327	.005	.039	-.144	.119
France	327	.006	.053	-.192	.183
Large Growth	327	.009	.061	-.227	.153
Large Value	327	.008	.061	-.339	.279
Small Growth	327	.008	.065	-.299	.216
Small Value	327	.008	.074	-.386	.429

Panel B	DG				
	Observations	**Mean**	**Std. Dev.**	**Min**	**Max**
US	315	.005	.011	-.037	.049
UK	315	.002	.029	-.155	.140
France	315	.003	.060	-.425	.340
Large Growth	315	.009	.040	-.116	.211
Large Value	315	.005	.022	-.075	.073
Small Growth	315	.012	.052	-.125	.192
Small Value	315	.005	.034	-.131	.145

Table 1: Summary statistics for return and dividend growth for period from June 1995 to September 2022.
Note: Return and dividend growth constructed following Chen (2009)

Table 1 provides the summary statistics for return and DG for the seven indexes considered during the sample period. Internationally, the US observes on average the highest return, followed by France and then the UK. The US and France also see higher return standard deviation as compared to the UK, in line with the general notion of high risk high reward. Additionally, the US observes on average the highest DG, followed by France and then the UK. However, the US notes its DG standard deviation being the lowest amongst the three with France being the highest. Cross-sectionally, the four segments see similar level of return on average, albeit with Small Value observing higher standard deviation compared to the other three. In terms of DG, Large Growth and Small Growth both notice higher DG compared to its Value counterparts, and this pattern also follows to the standard deviation.

3.1.2 Predictable dummy variables

Given the probabilistic nature of the ML Logit regression, dummy variables must be generated from the data universe of 102 equity indexes. These indexes include, if available, the main large and small cap indexes traded on the local exchange representative of the countries' equity markets, as well as the country-specific FTSE large and small cap indexes which are subsets of the FTSE Global Equity Index Series covering 98% of the global investable market capitalization (London Stock Exchange Group, 2024). With each index, regressions following equation (7) are run with DP as the predictor and return and DG as the dependent variables. The regressions make use of Newey and West (1987) standard errors to adhere to OLS assumptions with the number lags following the rule of thumb of Stock and Watson (2019), which comes out to be 4 with the time period considered (refer to section 4.3 and Appendix B for detailed discussion of the methodology). The dummy variable for predictable return takes a value of 1 if the coefficient of DP is significant at the 5% level in the regression with return as the dependent variable and 0 otherwise. The same procedure applies to regressions where DG is the dependent variable. This effectively generates two series of dummy variables, indicating whether the index sees DP being a successful predictor of return and/or DG, and thus facilitating the use of the ML Logit regression in determining which factors affect the predictability.

3.2 Higher-level data

3.2.1 Recession indicator

The data for the recession indicators for the 32 countries examined is of monthly frequency and sourced from Federal Reserve Bank of St. Louis (2024). The data is different series of binary dummy variable taking value of 1 is the month is classified as during a period of recession, 0 otherwise, for the different countries. The time series will be used in the OLS regressions while the proportion of months classified as recession will be computed for use in the cross-sectional ML Logit regressions. The indicators follow the "midpoint" method depicting times of economic contraction as the period between the midpoint of the peak and the midpoint of the trough – as shown below in Figure 1:

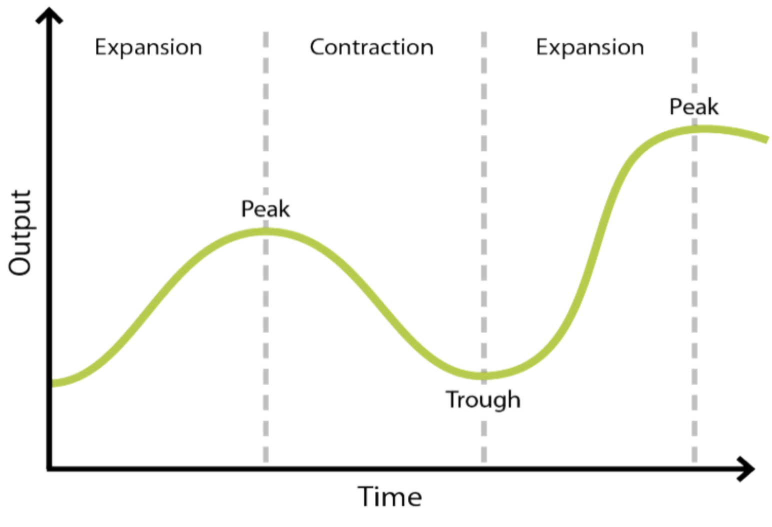

Figure 1: The business cycle illustratively with times of expansion and contraction

Note: Sourced from Reserve Bank of Australia (2023)

The series is an interpretation of the Organization of Economic Development (OECD) Composite Leading Indicators: Reference Turning Points and Component Series, where the Gross Domestic Product (GDP) is used for identification of the business cycle turning points (Organization of Economic Development, 2024). In addition to individual country series, there are also indicators for groups of countries that are frequently regarded together such as the Group of Seven (G7), which the US, the UK and France are a part of. Moreover, the US also has business cycle dates from the National Bureau of Economic Research (NBER) where a wide array of measures are used to determine the turning points, including real personal consumption expenditures and industrial production amongst others (National Bureau of Economic Research, 2024). Therefore, additional OLS regressions will be run with the G7 indicator internationally and NBER indicator cross-sectionally to test the results' robustness to different recession indicator specifications.

3.2.2 Term spread

Data to calculate the term spread was retrieved from Refinitive Workspace (2024b). More specifically, data on the 10-year government treasury bond yield and the 2-year government treasury bond yield was obtained and their difference is computed to get the 10-2 year term spread. The time series will be used in the OLS regressions for the three countries considered, while average term spread will be computed for the full 32 countries for use in the ML Logit regression. The inclusion of the term spread follows Fama and French (1989), where the authors argue that the term spread tracks a different component of equity return than DP, with the former tracking a maturity premium associated with long-term assets while the latter tracking a component that varies with business-conditions risk. More generally, the term spread is also related to the business cycle through the yield curve, a graph plotting yield against maturity usually of government bonds. An upward-sloping curve usually indicates times of economic expansion while an inverted, downward-sloping, curve usually entails times of recession.

3.2.3 Inflation

Data on inflation rates was sourced from the Global Database of Inflation from Ha et al. (2023), comprising of six measures of inflation for up to 209 countries. This paper uses the headline Consumer Price Index (CPI), the full figure reported with all the components of the basket of consumer goods, as opposed to other partial segments like food or energy to reflect the complete picture of price development. From the CPI, the 12-month percentage change is calculated as the measure for inflation rates. The time series will again be used in the OLS regressions while the average inflation rates will be computed for use in the ML Logit regression. The motivation for inflation follows Campbell and Vuolteenaho (2004) where the authors provide evidence for the Modigliani and Cohn (1979) hypothesis, investors incorrectly using nominal discount rates when discounting real cashflows, thus implying that stock mispricing can be explained by varying general price levels.

3.2.4 Oil price uncertainty

Data to calculate oil price uncertainty was downloaded from US Energy Information Administration (2024). More specifically, daily spot prices of West Texas Intermediate crude oil were downloaded. Afterwards, the monthly uncertainty in oil prices was calculated following the methodology of Sadorsky (2008) given in equation (1):

$$\mathrm{Oil_t} = \sqrt{\frac{1}{\mathrm{N}-1} \cdot \sum_{\mathrm{t}=1}^{\mathrm{N}} \left(\mathrm{r_t} - \mathrm{E(r_t)}\right)^2} \cdot \sqrt{\mathrm{N}} \tag{1}$$

where N denotes the number of days where a spot price was recorded in a month, $\mathrm{E(r_t)}$ denotes the average return measured across the time period considered, and $\mathrm{r_t}$ denotes the daily oil return computed using equation (2):

$$\mathrm{r_t} = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{2}$$

where $\mathrm{p_t}$ and $\mathrm{p_{t-1}}$ denotes the spot price today and yesterday, respectively.

The motivation stems of this variable stems from Casassus and Higuera (2011), where the authors test for return predictive power of oil price changes, reporting strong evidence of predictability at short horizons that is robust to inclusion of other variables as well as out-sample tests, as well as voluminous literature on the interlink between equity return and oil prices (Sadorsky, 1999; Park & Ratti, 2008; Joo & Park, 2021). Similar to term spread and inflation, the time series will be used in the OLS regressions. However, this variable will not be incorporated in the ML Logit regression as it is a single series proxying for the global oil price uncertainty, hence reducing it to the cross-sectional level would result in only one value and thus making it unusable.

CHAPTER 4 Methodology

4.1 Framework

As mentioned in section 2.1, one of the most well-known applications of the relationship between return, DP, and DG is the Gordon (1962) growth model:

$$P_t = D_t \sum_{t=1}^{\infty} \frac{(1+g)^t}{(1+r)^t} = \frac{D_{t+1}}{r-g} \tag{3}$$

where P_t denotes the price of a stock today, D_{t+1} denotes the dividend in the next period, r denotes the required rate of return, and g denotes the growth rate of dividends.

With some simple manipulation, one can rearrange equation (3) to get DP as the rate of return minus the growth rate, providing the basic intuition of how DP variation is decomposed into information from return and cashflows:

$$\frac{D_{t+1}}{P_t} = r - g \tag{4}$$

However, a major assumption in the model above is that both return and DG are assumed to be constant. Campbell and Shiller (1988) in their work relaxed this assumption, allowing analysis of DP variation through time in the context of return and DG. More precisely, they first obtain a log-linear approximation of return:

$$DP_t \approx -\kappa + \rho(DP_{t+1}) + R_{t+1} - DG_{t+1} \tag{5}$$

where DP_t denotes the log dividend yield, DG_{t+1} denotes the log dividend growth rate, R_{t+1} denotes the log return, and κ and ρ are linearization constants.

Iterating equation (5) forward, the dividend-ratio model/present value identity is obtained:

$$DP_t \approx -\frac{\kappa}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j R_{t+1+j} - E_t \sum_{j=0}^{\infty} \rho^j DG_{t+1+j} \tag{6}$$

Following equation (6), we see that both return and DG are now time-varying and weighted sums are taken to arrive at the current DP, hence it is also referred to as the dynamic Gordon (1962) growth model. Furthermore, as the two measures now vary through time, the identity proposes a theoretical motivation for the use of DP in predicting the two measures. Assuming constant expected DG, if expected return increase, stock price would decrease as now dividends are discounted at a higher rate and increase DP as a result, thus a positive relationship between DP and return. On the other hand, assuming constant expected return, if expected DG increase, stock price would increase as now more dividends would be paid and decrease DP as a result, thus a negative relationship between DP and DG. This prompts the broad regression equation that capture the relationships mentioned above and serve as the basis for the analysis of this paper:

$$y_{t+1} = \beta_0 + \beta_1 DP_t + \varepsilon \tag{7}$$

where y is either return or DG.

4.2 Variable construction

The construction of return, DP and DG used in this paper follows the methodology used by Chen (2009). Note the use of the logarithm transformation adheres to the dividend-ratio model by Campbell and Shiller (1988) aforementioned.

First, denote the monthly return of an index as:

$$R_t = \ln\left(\frac{P_t + D_t}{P_{t-1}}\right) \tag{8}$$

where P_t denotes the price of the index and D_t denotes the monthly dividends where, following Golez (2014), is calculated by taking the "difference between return on the total return index and the return on the price index multiplied by the lagged price index" (p. 796).

The dividend yield (DP) is calculated as:

$$DP_t = \ln\left(\frac{D_t^{12}}{P_t}\right) \tag{9}$$

where D_t^{12} is the simple sum of the dividends in the past 12 months, $D_t^{12} = \sum_{i=0}^{11} D_{t-i}$.

The dividend growth rate (DG) is calculated as:

$$DG_t = \ln\left(\frac{D_t^{12}}{D_{t-1}^{12}}\right) \tag{10}$$

Bear in mind the formulation above assumes no dividend reinvestment, contrasting with another popular specification where dividends received are reinvested at the stock market return. Koijen and Van Nieuwerburgh (2011) examine the two specifications and found substantial differences between the mean and the volatility of the DG series. Chen (2009) furthermore advises against reinvesting dividends as then information about return would be infused into DG, thus "burying the predictability" (p. 129). of the two measures. Therefore, this paper assumes no reinvestment to clearly distinguish the efficacy of DP in predicting return and/or DG.

4.3 Ordinary Least Squares (OLS) regression

The first technique employed in this paper to answer Hypothesis 1 is time series OLS regressions, run at monthly frequency. The full regression equation is as follows:

$$\begin{aligned} \mathrm{y}_{\mathrm{t+1}} = \beta_0 + \beta_1 \mathrm{DP}_\mathrm{t} + \beta_2 \mathrm{Recession}_\mathrm{t} + \beta_3 \mathrm{DP}_\mathrm{t} \times \mathrm{Recession}_\mathrm{t} + \beta_4 \mathrm{Term}_\mathrm{t} \\ + \beta_5 \mathrm{Inflation}_\mathrm{t} + \beta_6 \mathrm{Oil}_\mathrm{t} + \varepsilon \end{aligned} \tag{11}$$

where $\mathrm{y}_{\mathrm{t+1}}$ denotes either return or DG in light of Cochrane (2007), DP_t denotes the dividend yield, $\mathrm{Recession}_\mathrm{t}$ denotes the OECD individual recession indicator following Golez and Koudijs (2018) taking a value of 1 if the month in question is classified as during a period of economic contraction, and an interaction term between the two is included to measure the moderation effect of periods of recession on the predicting usage of DP. The control variables include Term_t denoting the spread between the 10-year government treasury bond and the 2-year government treasury bond, $\mathrm{Inflation}_\mathrm{t}$ denoting the 12-month percentage change in the headline CPI, and Oil_t denoting the oil price uncertainty computed following the methodology of Sadorsky (2008).

To examine international heterogeneity, regressions will be run on three large-cap indexes: the S&P500, FTSE100, and CAC40 representing the three countries the US, the UK and France respectively. The choice of the US serves for comparability with the main stream of literature focusing on the US such as Chen (2009), Golez and Koudijs (2018), whereas the motivation for the UK and France follows Cornell (2014) where these two countries exhibit opposite trends in predictability. Cross-sectionally, analysis will be conducted on four US indexes proxying for the four segments split in terms of size and value/growth following Maio and Santa-Clara (2015): S&P500 Pure Growth for Large Growth stocks, S&P500 Pure Value for Large Value stocks, S&P600 Pure Growth for Small Growth stocks, and S&P600 Pure Value for Small Value stocks.

An important consideration when using OLS regression is whether its assumptions are met – a failure to do so may result in biased and inconsistent results. More specifically, the failure to adhere to the assumptions of homoskedasticity and error independence can result in incorrect standard errors of the estimated coefficients, leading to incorrect inferences. Hence, statistical tests were performed, and the results indicate violations in several of the indexes concerned (details of the tests are presented and elaborated upon in Appendix B). Therefore, the regressions will be conducted using Newey and West (1987) standard errors which can account for the presence of both heteroskedasticity and serial correlation, as similarly done by Chen (2009) and Golez and Koudijs (2018). With respect to the number of lags, it is determined to be 5 given the sample period considered following the rule of thumb provided by Stock and Watson (2019) where the number of lags m equals:

$$\mathrm{m} = \mathrm{int}\left(0.75\mathrm{T}^{\frac{1}{3}}\right) \tag{12}$$

with T being the number of observations.

Furthermore, given there are other specifications of the recession indicators as discussed in section 3.2.1, robustness tests will be conducted by means of additional OLS regressions to examine the validity of the results obtained with the OECD individual indicators. More precisely, the regression for the three countries will make use of the OECD G7 indicator as the US, the UK and France are all part of the Group of Seven, while regressions for the equity cross-sections will make use of the NBER indicator as the indexes concerned all belong to the US.

4.4 Multilevel (ML) Logit regression

The second technique used in the paper to answer Hypothesis 2 is Logit regressions, more specifically the ML variant of it. The motivation for using ML Logit lies in the nested structure of the data, as illustrated below.

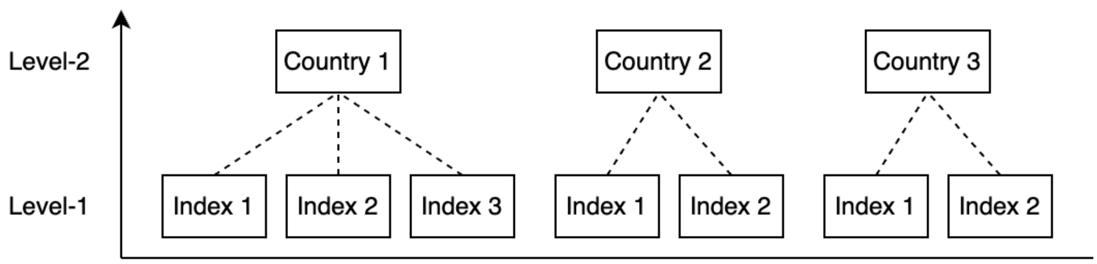

Figure 2: Visualization of nested data structure with multiple countries and indexes

As seen in Figure 2, the data contains multiple countries where each country have its own multiple indexes, resulting in this particular nested or hierarchal structure. With this structure comes two types of predictors: those that are on the individual index level (level-1) and those that are on the country level (level-2). Therefore, the assumption of error independence is likely to be violated as all indexes within the same country will have identical level-2 variables (note that Logit regressions are robust to violation of homoskedasticity in theory). Furthermore, Sommet and Morselli (2017) note that given such nested structure, “the odds that the outcome variable equals one … may vary from one cluster [country] to another” (p. 203). If regular Logit regressions are run, the model would overlook these country level differences and instead “pool” them together, potentially obscuring the resulting effects. As a result, this paper uses the ML Logit regression where a random intercept variance is additionally estimated to account for such differences in level-2 predictors. Nevertheless, an extra estimated parameter, if unnecessary, may negatively impact the entire model performance. Therefore, statistical tests comparing regular Logit and ML Logit were conducted and the results, which are reported in Appendix C, justify the use of ML Logit over regular Logit.

Similarly to OLS, regressions will be run for both return and DG with the following equation:

$$\begin{aligned} y_{ij} = \beta_{00} + \beta_{01}\text{Percent Recession}_{ij} + \beta_{02}\text{Avg. Inflation}_{ij} + \beta_{03}\text{Avg. Term}_{ij} + \beta_{10}\text{Small}_{ij} \\ + \beta_{20}\text{Std. Dev}_{ij} + \mu_{0j} + \varepsilon \end{aligned} \tag{13}$$

where y_{ij} denotes the dummy for whether index i in country j sees either its return or DG being predictable by DP.

Level-2 variables include $\text{Percent Recession}_{ij}$ denoting the proportion of months that are considered during economic contractions derived from the OECD individual recession indicators. This variable follows the notion of increased return predictability during recessions as aforementioned. Other variables include $\text{Avg. Inflation}_{ij}$ denoting the average of the inflation rates calculated as the 12-month percentage change of the headline CPI and Avg. Term_{ij} denoting the average term spread between the 10-year government treasury bond and the 2-year government treasury.

Level-1 variables include a dummy variable Small_{ij} indicating whether the index is small-cap or large-cap following the cross-sectional heterogeneity discussion. The value/growth dimension is not included as there are very few distinct indexes that are tailored clearly towards these factors. Std. Dev_{ij} which denotes the standard deviation of return when DG is the dependent variable and vice versa, following the argument from Chen (2009) where high return volatility and low DG volatility induce better predictability of return. The alternating of variables prevents information from the variables used in the construction of the dummies to seep into the analysis. Lastly, μ_{0j} is the random intercept variance that accounts for level-2 differences in affecting the odds of the outcome being one as opposed to zero. Note that there is no variable for oil price uncertainty as there is only one series, hence there is zero variation across the indexes (analogously a level-3 variable).

CHAPTER 5 Results & Discussion

5.1 Hypothesis 1

5.1.1 International heterogeneity

The results for the OLS regressions run on the three countries the US, the UK and France are presented in Table 2 with two panels A and B. Panel A presents the results where the dependent variable is return, and Panel B is for where DG is the dependent variable.

5.1.1.1 General predictability trends

In terms of the overall efficacy of DP in predicting return, Panel A in Table 2 suggests that the US sees the highest predictive power, with the coefficient of DP in model (2) and (3) being significant at the 5% and 1% level respectively. All the coefficients across all models also observe a positive sign, which correctly follows the theoretical motivation discussed in section 4.1. The UK comes second with somewhat mixed results. While all coefficients have the correct positive sign, only that of model (3) and (4) are significant, albeit only at the 10% level. France delivers the worst results in terms of return predictability, with all insignificant coefficients of DP and three of them having the incorrect negative sign. The fit of the model also tells a similar story where both the R^2 and adjusted R^2 for the base model (1) decrease across the US, the UK and France, with the US observing the highest fit across all models.

When analyzing Panel B in Table 2 for DG predictability, the opposite pattern emerges. The US sees insignificant DP coefficients across all models, with even negative adjusted R^2 of -0.002 in the base model (1). The UK observes all correctly negatively signed DP coefficients yet only that of the first two models were significant. France, on the contrary, exhibits strong DG predictability with all significant negative coefficients at 5% (with two instances even significant at 1%). The fit of the model also reflects this pattern, with the worst fit in terms of R^2 and adjusted R^2 belonging to the US, while the UK and France see substantial improvements.

Given the analysis, it can be seen that the stylized fact, US equity return is predictable by DP but DG is not, still holds for this recent sample period. Additionally, the results further reinstate that the stylized fact is only a phenomenon pertaining to the US and not an international one, where evidence in this paper roughly follows that of Cornell (2014): the UK only offers relatively weak evidence for return predictability while France shows little to none. More overarchingly, the results is a testament to Cochrane (2007)'s call for the need to also focus on DG predictability as theoretically it is "the flip side of the coin" to return predictability, where one observes the opposite pattern for DG predictability in the three countries concerned. With the argument by Chen (2009) where higher volatility of return and low volatility of DG is the reason why return is predictable and vice versa for DG, the analysis give mixed

Panel A	Return$_{t+1}$											
	United States				**United Kingdom**				**France**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DP$_t$	0.03	0.04**	0.04***	0.02	0.01	0.01	0.03*	0.03*	-0.00	0.01	-0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Recession$_t$		-0.02***	-0.07	-0.07		-0.01	-0.13	-0.14		-0.01*	0.13	0.11
		(0.01)	(0.12)	(0.11)		(0.01)	(0.09)	(0.10)		(0.01)	(0.09)	(0.09)
D/P$_t$ ×			-0.01	-0.01			-0.03	-0.04			0.04	0.04
Recession$_t$			(0.03)	(0.03)			(0.03)	(0.03)			(0.03)	(0.02)
Term$_t$				-0.00				0.00				0.01**
				(0.00)				(0.00)				(0.01)
Inflation$_t$				-0.62***				-0.28				-1.06***
				(0.18)				(0.18)				(0.23)
Oil$_t$				0.11				0.08				0.07*
				(0.07)				(0.05)				(0.04)
Constant	0.11	0.16**	0.19***	0.13**	0.05	0.04	0.11**	0.11*	-0.00	0.04	-0.03	-0.07
	(0.08)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)
Observations	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.014	0.054	0.055	0.104	0.005	0.013	0.020	0.034	0.000	0.013	0.024	0.081
Adjusted R^2	0.011	0.048	0.045	0.087	0.002	0.007	0.011	0.016	-0.003	0.007	0.014	0.063

Panel B	DG$_{t+1}$											
	United States				**United Kingdom**				**France**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DP$_t$	-0.00	-0.00	-0.00	-0.00	-0.02*	-0.03**	-0.03	-0.03	-0.04***	-0.04***	-0.04**	-0.05**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Recession$_t$		-0.00	0.02	0.02		-0.01***	-0.02	0.03		-0.01	-0.02	0.04
		(0.00)	(0.05)	(0.05)		(0.00)	(0.07)	(0.06)		(0.01)	(0.08)	(0.10)
D/P$_t$ ×			0.01	0.01			-0.00	0.01			-0.01	0.01
Recession$_t$			(0.01)	(0.01)			(0.02)	(0.02)			(0.02)	(0.03)
Term$_t$				0.00				0.00				0.00
				(0.00)				(0.00)				(0.00)
Inflation$_t$				0.10				0.21*				0.44
				(0.06)				(0.13)				(0.28)
Oil$_t$				-0.01				-0.16***				-0.44***
				(0.01)				(0.03)				(0.11)
Constant	-0.00	0.00	-0.01	-0.00	-0.07*	-0.09**	-0.08	-0.10	-0.15***	-0.13***	-0.12**	-0.16**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)	(0.06)	(0.07)	(0.04)	(0.04)	(0.05)	(0.07)
Observations	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.001	0.019	0.022	0.040	0.023	0.054	0.054	0.115	0.044	0.046	0.047	0.153
Adjusted R^2	-0.002	0.013	0.012	0.022	0.020	0.048	0.045	0.097	0.041	0.040	0.037	0.137

Table 2: OLS Regression results of return and dividend growth against dividend yield, recession dummy using OECD individual indicator, an interaction term between the dividend yield and recession dummy, term spread, inflation and oil price uncertainty for the indexes S&P500, FTSE100, and CAC40 representing the countries the United States, the United Kingdom, and France. Sample period of June 1995 – September 2022.

Note: Newey-West (1987) standard errors with 5 lags in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

results. Considering the summary statistics provided in Table 1, while the US observes standard deviation of 0.045 for return and 0.011 for DG which may explain its evidence for return predictability, France still shows strong evidence for predictability in DG and very little in return despite observing relatively similar standard deviations of 0.053 for return and 0.060 for DG.

5.1.1.2 Recessionary periods

Moving on to the analysis of the business cycle, Panel A shows the coefficients of the recession dummy variable in the regressions with return as the outcome variable are mostly negative across the three countries, with only models (3) and (4) of France having positive signs. The significant coefficients are also only the negative ones, with model (2) of the US at 1% and model (2) of France at 10%. This comes at a surprise as given the well documented countercyclical nature of return, one would expect the sign of the dummy variable to be positive as found in Golez and Koudijs (2018).

A possible explanation for this apparent contradiction is that the OLS regressions run in Golez and Koudijs (2018) are of annual frequency while this paper uses monthly frequency. In their paper, Golez and Koudijs (2018) utilizes the monthly recession dummy from NBER not for the regression directly but for classifying a year as a recession if at least six months within that year are noted as part of an economic contraction. This procedure ensures that the recession periods are, to a certain extent, important instances that have substantial impact on the economy, as opposed to just minor fluctuations following the business cycle. Golez and Koudijs (2018) further note that the dating of recession happens ex-post hence information is "not necessarily available in real time" (p. 260), which is even more problematic when the shorter monthly frequency is considered.

Moving on to the moderation effect, the interaction term between the recession dummy and DP observe mixed results. For all three countries, the coefficients are insignificant with the sign being negative for the US and the UK, and positive for France. These "underwhelming" results may be attributable to the unclear effect of the recession dummy as mentioned above. Looking at the model fit, the US observes a drop in adjusted R^2 from 0.048 to 0.045 when moving from model (2) to model (3), while the UK and France both observe an increase in adjusted R^2 from 0.007 to 0.011 and 0.007 to 0.014, respectively. This might indicate the extent which recession moderates DP is less in countries where the relationship is clear, as DP might already be closely tracking the variation in return throughout economic fluctuations. Nevertheless, the slopes have different signs and are insignificant therefore any potential inferences remain inconclusive.

5.1.1.3 Control variables and robustness test

Term spread sees negative coefficient for the US and positive coefficients for the other two with 5% significance for France, consistent with the findings of Fama and French (1989) that term spread tracks a maturity premium. Inflation observes negative coefficients across the three countries, being significant in the US and France. The negative relationship is similar to results of Fama and Schwert (1977), and consistent with the findings of Campbell and Vuolteenaho (2004) on stock mispricing by investors with changing price level as discussed in section 3.2.3. Oil price uncertainty exhibits consistent positive slopes across the board and 10% significance in France, implying that in the sample increasing oil price uncertainty results in declines in stock prices hence higher return. The varying degrees of significance across the countries shows how different variables tracking return apply to different countries, further reinforcing the idea of international heterogeneity.

The results of the robustness test on the three countries are presented in Appendix D Table 1. When substituting for the OECD G7 recession indicator, the results generally tell the same story of the US having the best return predicting power of DP in contrast to the other two countries after considering both the regressions with return and DG as dependent variables. The recession dummies see little changes in the magnitude and significance of the coefficients, and the interaction terms exhibit the same patterns as well as the control variables. Therefore, the results of the OLS regressions in Table 2 is largely robust to the use of different recession indicator specification.

5.1.2 Equity cross-sections

The results for the OLS regressions run on the four equity cross-sections are presented in Table 3 with identical structure as that for the three countries in Table 2.

5.1.2.1 General predictability trends

When looking at return predictability, Large Growth stocks display the strongest evidence with correct positive slopes except for model (4), with that of model (1) and (2) being significant at 10% and 5%, respectively. The fit is also the highest amongst the four cross-sections, with the adjusted R^2 being 0.012 in the base model (1) and increasing to 0.078 in model (4). Large Value stocks exhibit mixed results, as although all coefficients are correctly signed and those in models (3) and (4) are significant at 5%, the fit is rather poor when only DP is used with adjusted R^2 in model (1) even being negative -0.003. The small-cap stocks show zero evidence of return predictability, with all coefficients being insignificant despite all correctly signed, and poor fit of the models with the adjusted R^2 all staying in the negatives until model (4). The results are in line with Maio and Santa-Clara (2015) where the authors also report stronger return predictability in large-cap stocks, especially Large Growth, while little evidence is found for small-cap stocks.

On the other hand, Large Growth stocks observe little DG predictability with most coefficients incorrectly signed, all insignificant, as well as poor fit in terms of (adjusted) R^2. Large Value stocks see

Panel A	Return$_{t+1}$															
	Large Growth				**Large Value**				**Small Growth**				**Small Value**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DP$_t$	0.02*	0.02**	0.01	-0.00	0.00	0.01	0.04**	0.04**	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Recession$_t$		-0.02***	0.07	0.06		-0.02*	-0.23	-0.27*		-0.01	-0.00	-0.10		-0.01	-0.04	-0.07
		(0.01)	(0.08)	(0.08)		(0.01)	(0.14)	(0.14)		(0.01)	(0.07)	(0.09)		(0.01)	(0.13)	(0.13)
D/P$_t$ ×			0.02	0.02			-0.06	-0.07*			0.00	-0.01			-0.01	-0.01
Recession$_t$			(0.02)	(0.02)			(0.04)	(0.04)			(0.01)	(0.02)			(0.03)	(0.03)
Term$_t$				0.00				0.01				0.00				0.01
				(0.00)				(0.01)				(0.00)				(0.01)
Inflation$_t$				-0.82***				-0.54**				-0.79***				-0.63*
				(0.25)				(0.24)				(0.23)				(0.32)
Oil$_t$				0.16**				0.14				0.17*				0.19
				(0.08)				(0.10)				(0.10)				(0.12)
Constant	0.09*	0.10**	0.05	0.01	0.01	0.04	0.16**	0.18***	0.03	0.04	0.03	0.07	0.01	0.01	0.03	0.06
	(0.05)	(0.04)	(0.06)	(0.05)	(0.10)	(0.09)	(0.08)	(0.07)	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)	(0.07)	(0.06)	(0.07)
Observations	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.016	0.038	0.043	0.096	0.000	0.014	0.029	0.070	0.002	0.006	0.006	0.056	0.000	0.002	0.002	0.038
Adjusted R^2	0.012	0.032	0.033	0.078	-0.003	0.008	0.020	0.052	-0.002	-0.001	-0.004	0.037	-0.003	-0.005	-0.008	0.020

Panel B	DG_{t+1}															
	Large Growth				**Large Value**				**Small Growth**				**Small Value**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\mathbf{DP_t}$	0.00	0.00	-0.01	0.00	-0.03***	-0.03***	-0.03***	-0.04***	-0.00	-0.00	0.00	0.00	-0.02***	-0.02***	-0.03**	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbf{Recession_t}$		-0.00	0.09	0.08		-0.00	-0.02	0.00		0.00	-0.04	-0.01		-0.00	0.02	0.03
		(0.01)	(0.07)	(0.07)		(0.00)	(0.04)	(0.04)		(0.01)	(0.07)	(0.07)		(0.01)	(0.00)	(0.05)
$\mathbf{D/P_t \times}$			0.02	0.02			-0.00	-0.00			-0.01	-0.00			0.01	0.01
$\mathbf{Recession_t}$			(0.01)	(0.01)			(0.01)	(0.01)			(0.01)	(0.01)			(0.01)	(0.01)
$\mathbf{Term_t}$				0.00				-0.00**				0.01**				-0.01
				(0.00)				(0.00)				(0.00)				(0.01)
$\mathbf{Inflation_t}$				0.63				0.23*				0.38				0.72***
				(0.41)				(0.12)				(0.27)				(0.18)
$\mathbf{Oil_t}$				-0.05**				-0.01				-0.01				-0.07**
				(0.02)				(0.02)				(0.03)				(0.03)
Constant	0.03	0.03	-0.02	-0.01	-0.12***	-0.12***	-0.11**	-0.13***	0.00	0.00	0.02	-0.00	-0.09***	-0.09***	-0.10**	-0.13***
	(0.04)	(0.04)	(0.06)	(0.06)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.06)	(0.06)	(0.03)	(0.02)	(0.04)	(0.04)
Observations	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315
$\mathbf{R^2}$	0.003	0.006	0.018	0.078	0.172	0.172	0.173	0.253	0.000	0.001	0.002	0.032	0.076	0.078	0.079	0.235
Adjusted $\mathbf{R^2}$	-0.000	-0.000	0.008	0.060	0.169	0.167	0.165	0.238	-0.003	-0.006	-0.007	0.013	0.073	0.072	0.070	0.220

Table 3: OLS Regression results of return and dividend growth against dividend yield, recession dummy using OECD individual indicator, an interaction term between the dividend yield and recession dummy, term spread, inflation and oil price uncertainty for the indexes S&P500 Pure Growth, S&P500 Pure Value, S&P600 Pure Growth, and S&P600 Pure Value representing the equity cross-sections Large Growth, Large Value, Small Growth, and Small Value. Sample period of June 1995 – September 2022.

Note: Newey-West (1987) standard errors with 5 lags in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

superior evidence for DG as all slopes are negative and 1% significant. The segment also sees superb fit with the adjusted R^2 ranging from 0.169 - 0.238, demonstrating that the significant slopes of models (3) and (4) in the return regressions are not products of the underlying return predictability of DP. Similarly, Small Value stocks observe significant negative slopes and strong model fit and again in line with Maio and Santa-Clara (2015) where they report the bulk of evidence for DG predictability in Small Value stocks, albeit expected given its lack of return predictability. Interestingly, Small Growth stocks observe poor DG predictability despite its little evidence for return predictability with insignificant DP slopes and negative adjusted R^2 up until model (4). This implies that, following the dividend-ratio model discussed extensively in sections 2.1 and 4.1, the variation of DP for Small Growth stocks holds no information on both return and DG.

When considering in conjunction with the summary statistics from Table 1, Large Growth stocks observe standard deviation of 0.061 for return and 0.040 for DG which may explain the evidence for its return predictability. However, the value stocks, which observe strong evidence of DG predictability and little to no evidence for that of return, actually see higher standard deviation for return than DG – Large Value observes 0.061 and 0.022 for return and DG, respectively, while Small Value sees 0.074 and 0.034. Combinedly with the similar analysis in section 5.1.1 for the different countries, the results show that the dynamics between the volatility of return and DG does not necessarily explain the presence of predictability as was put forth in the argument by Chen (2009).

5.1.2.2 Recessionary periods

Similar to Table 2, seven out of nine slopes of the recession dummy are negative. All the significant coefficients in model (2) of Large Growth at 1% and models (2) and (4) of Large Value at 10% are negative as well, which is in contrary to expectations given the countercyclical nature of returns mentioned in section 2.2. As before, the reason potentially lies in the monthly frequency used in the OLS regressions as opposed to annual frequency in Golez and Koudijs (2018). This shorter frequency allows small fluctuations of the business cycle to also be marked as recessions alongside prolonged periods with considerable impact. It also magnifies the lack of information on the current business cycle phase the economy is currently given the classification happens ex-post.

The interaction term between DP and the recession dummy once again reveals mixed results. The coefficients are negative for the value segments, positive for Large Growth stocks, and switches from positive to negative for Small Growth stocks. The only coefficient that is significant is that of model (4) for Large Value stocks, although this is only significant at the 10% level. In terms of model fit, only Large Value stocks see a substantial increase of adjusted R^2 upon including the interaction term, jumping from 0.008 to 0.020, which is expected given this is the only cross-section where the slope is significant. The remaining three see either a marginal improvement in the case of Large Growth stocks, or a deterioration in the case of the small-cap segments. This disputes the proposition of limited moderation effect when return predictability is present put forth in section 5.1.1.2, as Small Value stocks observe little evidence of return predictability yet still see a decrease in model fit when the interaction term is introduced. Overall, no clear conclusion can be reached as most of the coefficients are still insignificant and have different signs across the cross-sections.

5.1.2.3 Control variables and robustness test

Term spread sees positive coefficients across the board, again in line with Fama and French (1989), yet none of them are significant. Inflation observes all of its coefficients being negative and significant at 1% for the Growth dimension, 5% for Large Value stocks and 10% for Small Value stocks. The results for these two variables are consistent across all the cross-sections both in terms of sign and significance, which should not come as a surprise as all the indexes used are specific to the US. The coefficients for oil price uncertainty are all positive, and significant for Large Growth and Small Growth stocks at 5% and 10%, respectively. This implies stocks in the indexes concerned classified as exhibiting growth characteristics are in general more sensitive to uncertainty in oil prices.

The results of the robustness test on the four cross-sections are presented in Appendix D Table 2. Comparable to the international analysis, the results generally depict a similar story when substituting for the NBER recession indicator. The recession dummy now only see four of its nine coefficients being negative which although is more in line with the literature, none of the coefficients are significant. The magnitude, sign and significance of the three control variables are largely similar. If anything, the results paint a clearer image of that in Table 3. The coefficients of DP in models (3) and (4) of Large Value stocks are no longer significant as they previously were, which is more in line with its strong evidence of DG predictability. The interaction term of model (4) for Large Value stocks are also no longer significant, further indicating that no conclusive inferences can be derived.

5.1.3 Answer to Hypothesis 1

Based on the results in Table 2 and Table 3, the coefficients estimated for the interaction term between DP and recession dummy in predicting return does not give evidence for any moderating effect as proposed in Hypothesis 1. Namely, Hypothesis 1 predicts recessions to moderate the return predictability of DP such that the relationship is stronger in recessionary periods. By contrast, the results offer slopes that have different sign both internationally across the three countries and cross-sectionally across the four equity segments. Moreover, only one of the coefficients is significant, and yet it is only at the 10% level and is not robust to changes in the recession indicator. The fit of the models in terms of adjusted R^2 also generally do not improve upon the addition of the interaction term. Therefore, it is concluded that Hypothesis 1 is rejected given the lack of clear pattern in the effect as well as statistical significance.

5.2 Hypothesis 2

The results of the ML Logit regressions are presented in Table 4. As prior, the table is composed of Panel A where the dummy for return is the dependent variable and DG for Panel B.

5.1.1 Level-2 variables

In terms of the effect of the level-2 variables on the probability of an index's return being predictable by DP, results in Panel A of Table 4 shows that the proportion of recessionary periods is the only significant variable. Its coefficients are all positive and significant at 10% in model (1) and (2), and at 5% when run with the level-1 variables in model (4). This implies that an increase in the proportion of recessionary periods increases the chance of an index seeing its return predictable by DP. The result is statistically significant and is consistent with the notion of increased return predictability during downturns as shown by Golez and Koudijs (2018) and Henkel et al. (2011). It also defends the link between the business cycle and return predictability not exactly supported in Hypothesis 1, where although the recession dummy does not provide the "accurate" results due to the short frequency at the index level, it still correctly lines up with the theory discussed on a general level. When looking at DG, the coefficients are all negative which follows the intuition of DG predictability being the "flip side of the coin" to return, albeit being all insignificant.

The remaining two level-2 variables, average term spread and average inflation, have relatively large standard errors hence they are all insignificant, with the former seeing its coefficients switching signs between model (2) and (4) for both dependent variables and the latter seeing consistently positive coefficients in Panel A but switches signs in Panel B. These results entail that the variables do not act in accordance Cochrane (2007) where it has to be predictability of return or DG.

The results also explain the drop in model performance of the return regressions, where the AIC and BIC are lowest, 55.14 and 63.01 respectively, in model (1) where only proportion of recessionary periods is included. The information criteria increases upon inclusion of the other insignificant variables as additional but unnecessary parameters will be penalized, where the AIC is consistent around 58 across the remaining three models while BIC is highest for model (4) at 76.69 since BIC penalizes more for extra parameters.

5.1.2 Level-1 variables

Moving on to level-1 variables, results show that the dummy for small-cap index displays negative coefficients in the regressions with predictable return as the outcome, however these coefficients are insignificant. On the contrary, the coefficients in the regressions with predictable DG as the outcome are positive and significant at 10% in model (3) and 5% in model (4). These results imply that being a small-cap index increases the probability of seeing its DG being predictable by DP. This is in line with

Panel A	Predictable Return$_i$			
	(1)	(2)	(3)	(4)
Percent Recession$_i$	15.84*	17.20*		17.16**
	(8.84)	(9.45)		(8.20)
Avg. Inflation$_i$		27.65		34.52
		(32.48)		(27.65)
Avg. Term$_i$		0.07		-0.02
		(0.37)		(0.42)
Small$_i$			-1.66	-1.14
			(1.29)	(1.06)
Std. Dev. DG$_i$			-6.65	-20.51
			(7.99)	(16.11)
Constant	-11.17**	-12.49**	-5.58	-9.93**
	(5.06)	(5.78)	(4.06)	(4.77)
Observations	102	102	102	102
AIC	55.14	58.42	58.68	58.31
BIC	63.01	71.55	69.18	76.69

Panel B	Predictable DG$_i$			
	(1)	(2)	(3)	(4)
Percent Recession$_i$	-1.70	-2.59		-0.97
	(3.16)	(3.30)		(3.88)
Avg. Inflation$_i$		-11.47		12.54
		(16.02)		(23.10)
Avg. Term$_i$		0.05		-0.07
		(0.07)		(0.10)
Small$_i$			1.53*	1.65**
			(0.79)	(0.82)
Std. Dev. Return$_i$			-50.49*	-62.78*
			(25.99)	(32.62)
Constant	2.44*	3.11*	4.52**	5.29**
	(1.44)	(1.71)	(1.82)	(2.46)
Observations	102	102	102	102
AIC	106.58	109.71	100.48	105.61
BIC	114.45	122.84	110.98	123.99

Table 4: ML Logit Regression results of the Predictable Return (DG) dummy against percent of recessionary periods using OECD individual indicator, average inflation, average term spread, dummy variable for if index is small-cap, and standard deviation of DG (Return). Sample period of March 2007 – May 2022.

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the findings of Maio and Santa-Clara (2015) where their similar analysis on equity portfolios show DG predictability concentrating in small portfolios. The change in sign across the regressions for the two dependent variables also shows that the variable effect is "well-behaved" following the dichotomous nature of the topic.

The standard deviation of DG in the return regressions and the standard deviation of return in the DG regressions all exhibit negative coefficients, with the latter being significant at 10%. This is consistent with the argument proposed by Chen (2009) where higher volatility of return and low volatility of DG is the reason why return is predictable by DP in the US for the post-war period. Nevertheless, given the fact that statistical significance is only found in the DG regressions and 10% is relatively weak, no definitive conclusions can be reached, similar to the mixed results from the OLS analysis carried out in section 5.1.

In terms of model performance for the DG regressions, model (3) with only the level-1 variables observe the lowest AIC of 100.48 and BIC of 110.98, the other models with the addition of the level-2 variables exhibit higher values for both information criteria which makes sense as for DG regressions, only the level-1 variables are significant hence the "unnecessary" addition of the remaining variables is penalized by both information criteria.

5.1.3 Answer to Hypothesis 2

Based on the results of the ML Logit regressions, the coefficients of proportion of recessionary periods are positive and significant, at 10% for models (1) and (2) and 5% for model (4). This implies that an increase in the proportion of recessionary periods increases the probability an index sees its return being predictable by DP. These results fall in line with Hypothesis 2 which proposes that higher proportion of recessionary periods increase the chance of return being predictable by DP, following the prior evidence for increased return predictability in downturns of Golez and Koudijs (2018) and Henkel et al. (2011). Therefore it is concluded that Hypothesis 2 is accepted given its coefficients display the correct sign and statistical significance.

CHAPTER 6 Conclusion

This paper studies the dividend yield in predicting return in conjunction with the business cycle. On one hand, literature has noted theoretical motivations for the dividend yield to predict return and/or dividend growth. On the other, literature has also indicated a link between return itself and the business cycle, with return being countercyclical to economic fluctuations. However, little research has been carried out on the intersection of the two streams of works. More specifically, no research has explored the direct effect of the business cycle on return predictability with the dividend yield: how economic fluctuations might impact the return forecasting power of the dividend yield or whether the predictability is even present or not. Therefore, this paper aims to investigate such that with the central research question:

“How does the business cycle affect the efficacy of the dividend yield in predicting return?”

To answer the question, Ordinary Least Squares regressions are run with return and dividend growth on the dividend yield, a dummy variable indicating periods classified as recessions, and an interaction term between the two. The results show that there is no evidence of recessions moderating the effect of the dividend yield in predicting return. Additionally, dummy variables indicating whether an index sees its return or dividend growth being predictable by the dividend yield were constructed. These are subsequently fed into Multilevel Logit regressions with the proportion of recessionary periods calculated from the recession indicator dummies. The results show that there is a statistically significant positive effect of recessions on the probability of predictable return. That is, an increase in the proportion of recessionary periods increases the probability of an index seeing its return being predictable by the dividend yield.

The findings of the study suggest that recessions do not impact the dividend yield in predicting return on a low and intricate level. The insignificant interaction terms show that the forecasting effect of the dividend yield on return is not dependent on which phase of the business cycle the economy is in currently. However, on a more general scale, periods of economic downturn do impact the chance of return being predictable by the dividend yield. The results point to a positive relationship between the proportion of recessionary periods and the probability an index sees its dividend yield predicting return, providing evidence for the notion of increased return predictability in downturns noted in literature. Combinedly, the findings show that the dividend yield is able to track variation in return better during times of economic contraction, but its forecasting effect is not altered when in such periods.

6.1 Limitations

A major limitation of the study lies in the multiple constraints when cultivating the data universe. Firstly, the price and total return index must be available for each equity index. Furthermore, the country of the equity indexes must have data for the recession indicators, headline CPI as well as two different government treasury bond yields to compute the term spread. On top of this, all data must coincide for a reasonably long period such that predictability can be tested. This results in the humble 102 observations between a relatively limited time period from March 2007 to May 2022 for the Multilevel Logit regressions, hence any results obtained must be treated with caution.

Another limitation stemming from these constraints is the lack of control variables from other domains. Literature notes a wide range of factors from other disciplines that can influence return other than the interest rates and macroeconomic ones in this paper, such as implied correlation from derivatives market (Driessen et al., 2012) and new year optimism from behavioral finance (Bouman & Jacobsen, 2002). Inclusion of these variables would have allowed to account for these factors from the different domains, yet would have gravely damaged the number of observations.

6.2 Future research

For future research, a possible suggestion is to examine the predictability at a lower level, such as on a scale of industries or companies. At the current level of equity index, the constituents of the indexes are regarded as a single observation, with no attention paid to the composition of the companies belonging to the index. It might be that indexes exhibiting different predictability trends see different underlying companies operating in different fields, and these dissimilarities might be the force driving the observed trends. Consequently, analysis at a lower level will allow the models to account for these industry-specific or firm-specific factors, expanding our understanding of what causes return to be predictable by the dividend yield and what does not.

Another suggestion for upcoming research is to perform the analysis in sub-periods. Chen (2009) notes that return predictability seems to have only materialized after the second World War and not before. This shows that these predictability trends are not consistent but subjected to changes through time. Therefore, investigation at smaller intervals within the main time period will give insights into which specific episode(s) of the business cycle is driving the trends observed. Given that modern times have observed drastic changes to the financial landscape such as the subprime mortgage crisis of 2008 or quantitative easing following the COVID-19 pandemic, analysis in sub-periods will further allow the study of how the relationship observed between return predictability and economic fluctuations interact with these specific financial settings.

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APPENDIX A Equity index used in ML Logit regressions

Index	Country	Size
S&P500	US	Large
S&P600	US	Small
Dow Jones	US	Large
Russell2000	US	Small
FTSE US	US	Large
FTSE US Small	US	Small
FTSE Germany	Germany	Large
FTSE Germany Small	Germany	Small
FTSE100	UK	Large
FTSE Small Cap	UK	Small
FTSE UK	UK	Large
FTSE UK Small	UK	Small
CAC40	France	Large
CAC Small	France	Small
FTSE France	France	Large
FTSE France Small	France	Small
AEX	Netherlands	Large
AScX	Netherlands	Small
FTSE Netherlands	Netherlands	Large
FTSE Netherlands Small	Netherlands	Small
Topix100	Japan	Large
Topix Small	Japan	Small
FTSE Japan	Japan	Large
FTSE Japan Small	Japan	Small
FTSE Brazil	Brazil	Large
FTSE Brazil Small	Brazil	Small
FTSE Korea	Korea	Large
FTSE Korea Small	Korea	Small
Nifty500	India	Large
FTSE India	India	Large
FTSE India Small	India	Small
FTSE MIB	Italy	Large
FTSE Italy	Italy	Large
FTSE Italy Small	Italy	Small

S&P/ASX 200	Australia	Large
ASX Small Ordinaries	Australia	Small
FTSE Australia	Australia	Large
MSCI Australia Small	Australia	Small
Bel20	Belgium	Large
FTSE Belgium	Belgium	Large
FTSE Belgium Small	Belgium	Small
TSX60	Canada	Large
S&P Canada Small	Canada	Small
FTSE Canada	Canada	Large
FTSE Canada Small	Canada	Small
FTSE Chile	Chile	Large
FTSE Chile Small	Chile	Small
FTSE Indonesia	Indonesia	Large
FTSE Indonesia Small	Indonesia	Small
IPC (Bolsa)	Mexico	Large
FTSE Mexico	Mexico	Large
FTSE Mexico Small	Mexico	Small
OMXS30	Sweden	Large
OMXS Small Cap	Sweden	Small
FTSE Sweden	Sweden	Large
FTSE Sweden Small	Sweden	Small
FTSE Turkey	Turkey	Large
FTSE Turkey Small	Turkey	Small
OMXC20	Denmark	Large
OMXC Small Cap	Denmark	Small
FTSE Denmark	Denmark	Large
FTSE Denmark Small	Denmark	Small
PSI-20	Portugal	Large
FTSE Portugal	Portugal	Large
FTSE Portugal Small	Portugal	Small
SE PX	Czech Republic	Large
FTSE Czech	Czech Republic	Large
Wig20	Poland	Large
FTSE Poland	Poland	Large
FTSE Poland Small	Poland	Small

IBEX35	Spain	Large
FTSE Spain	Spain	Large
FTSE Spain Small	Spain	Small
OMX Helsinki 25	Finland	Large
OMX Helsinki Small Cap	Finland	Small
FTSE Finland	Finland	Large
FTSE Finland Small	Finland	Small
SMI	Switzerland	Large
FTSE Switzerland	Switzerland	Large
FTSE Switzerland Small	Switzerland	Small
ATX	Austria	Large
FTSE Austria	Austria	Large
FTSE Austria Small	Austria	Small
FTSE Norway	Norway	Large
FTSE Norway Small	Norway	Small
ISEQ20	Ireland	Large
ISEQ Small	Ireland	Small
FTSE Ireland	Ireland	Large
FTSE Ireland Small	Ireland	Small
CSI300	China	Large
FTSE China	China	Large
FTSE China Small	China	Small
Athex Composite	Greece	Large
FTSE Greece	Greece	Large
FTSE Greece Small	Greece	Small
FTSE/JSE Top 40	South Africa	Large
FTSE South Africa	South Africa	Large
FTSE South Africa Small	South Africa	Small
MOEX	Russia	Large
RTS	Russia	Large
FTSE Russia	Russia	Large
FTSE Russia	Russia	Small

Appendix A: List of equity indexes and its corresponding country and size used in the Multilevel Logit regressions.

APPENDIX B OLS regression examination

As mentioned in section 4.2, one must consider the assumptions before conducting OLS regressions. Specifically, the assumption of homoskedasticity, defined by Brooks (2019) as “variance of the errors is constant” (p. 257), and the assumption of error independence, defined as “errors are uncorrelated with one another” (p. 264), are both required to obtain correct standard errors and facilitate correct inferences. Therefore, statistical tests were run to determine whether there are any assumption violations.

The first test conducted is the White (1980) test targeting the homoskedasticity assumption. This test examines whether the variance of the residuals is related to the independent variables, with the null of homoskedasticity. The second test conducted is the Breusch (1978) - Godfrey (1978) test targeting the assumption of error independence. This test examines whether the residuals on independent variables are related to the lagged residuals, with the null of no serial correlation. Rejection of both tests indicate violation of the respective assumption. These tests were run on the initial base model following equation (7) with both return and DG as the dependent variable for the seven indexes concerned, and their P-values are reported in the table below.

Return		
Index	**White test**	**Breusch-Godfrey test**
S&P500	**0.000**	0.482
CAC40	0.281	0.251
FTSE100	**0.013**	0.694
Large Growth	**0.000**	0.728
Large Value	**0.000**	**0.015**
Small Growth	**0.004**	0.502
Small Value	**0.000**	**0.047**
DG		
Index	**White test**	**Breusch-Godfrey test**
S&P500	**0.000**	**0.016**
CAC40	0.094	0.927
FTSE100	**0.000**	0.839
Large Growth	**0.000**	**0.000**
Large Value	0.379	**0.001**
Small Growth	0.488	0.176
Small Value	0.095	**0.000**

Appendix B: P-values of White test homoskedasticity and Breusch-Godfrey test for errors independence.
Note: Bolded values significant at 5% level.

As seen in the table, almost all of the indexes violate at least one of the two assumptions tested in at least one of the two regressions considered, making it necessary to address such concerns. Therefore, the OLS regressions in this paper make use of the Newey and West (1987) standard errors where it accounts for both assumptions of homoskedasticity and serial correlation in order to arrive at more accurate standard errors following similar usage in Chen (2009) and Golez and Koudijs (2018). When using Newey and West (1987) standard errors, the number of lags must be specified, and this is determined following the rule of thumb provided by Stock and Watson (2019) as in equation (12) resulting in the use of 5 lags.

APPENDIX C ML Logit regression examination

Given the binary nature of the dependent variable, regular OLS regressions are no longer suitable as it can result in probabilities either larger than one or smaller than zero. This results in the need for the Logit regression, where a cumulative logistic distribution is used to fit the regression model according to an S-shape as opposed to a straight line as in OLS, effectively bounding the outcome within the (0, 1) interval, (Brooks, 2019).

However, as mentioned in section 4.4, the nature of the data follows a nested structure, where there are multiple countries, each with their own respective set of indexes, potentially violating the errors independence assumption. Additionally, Sommet and Morselli (2017) note that different clusters themselves may have different impact on the odds of the outcome variable being one rather than zero. Therefore, they propose an inclusion of an extra estimated random intercept variance that differ across the countries, namely the Multilevel (ML) Logit, to account for such country-level differences as opposed to regular Logit where it would "pool" the observations together and ignore the country level.

To formally assess the two, the likelihood-ratio (LR) test is used. The LR test uses the likelihoods of the two models in question, one restricted that is "nested" in the full one, and compare whether the addition of additional parameters see an increase in fit that is justifiable. In this specific context, the restricted model refers to the regular Logit while the full model refers to the ML Logit, as the latter is the former with an additional parameter being the estimated random intercept variance. Rejection of the test indicates that the addition of the extra parameters is justified as it "sufficiently" increases the fit of the model. The test is performed for the different model specifications conducted in the paper using the Logit and ML Logit models, with results depicted below:

	Model			
Dependent Variable	(1)	(2)	(3)	(4)
Predictable Return	**0.005**	**0.009**	**0.001**	0.072
Predictable DG	**0.050**	0.067	**0.037**	**0.043**

Appendix C: P-values of likelihood-ratio test comparing Multilevel Logit with regular Logit.

Note: Model numbers follow that in results Table 4. Bolded values significant at 5% level.

As seen in the table, the eight tests for both dependent variables show six which have P-values that are significant at the 5% level. The remaining tests are also significant at the 10% level. Given the evidence, the addition of the estimated random intercept variance significantly increases the fit of the models, therefore the use of the ML Logit regression is justified and is employed for the analysis of the binary dependent variables in the paper.

APPENDIX D OLS Regression robustness test: alternative recession indicators

Panel A	$Return_{t+1}$											
	United States				United Kingdom				France			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DP_t	0.03	0.03	0.03^{***}	0.02	0.01	0.01	0.03^{**}	0.03^{**}	-0.00	-0.00	-0.01	-0.03^{**}
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Recession_t$		-0.01^{**}	-0.06	-0.07		-0.01^{**}	-0.09	-0.11		-0.02^{***}	0.05	0.06
		(0.01)	(0.12)	(0.11)		(0.01)	(0.07)	(0.08)		(0.01)	(0.08)	(0.06)
$D/P_t \times$			-0.01	-0.01			-0.02	-0.03			0.02	0.02
$Recession_t$			(0.03)	(0.03)			(0.02)	(0.02)			(0.02)	(0.02)
$Term_t$				-0.00				0.00				0.01^{**}
				(0.00)				(0.00)				(0.00)
$Inflation_t$				-0.59^{***}				-0.29				-0.94^{***}
				(0.20)				(0.18)				(0.27)
Oil_t				0.11^{*}				0.07^{**}				0.09^{***}
				(0.06)				(0.04)				(0.03)
Constant	0.11	0.12^{*}	0.15^{***}	0.11^{*}	0.05	0.05	0.10^{**}	0.11^{**}	-0.00	0.01	-0.03	-0.08^{*}
	(0.08)	(0.07)	(0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.014	0.035	0.036	0.085	0.005	0.024	0.028	0.042	0.000	0.027	0.030	0.078
Adjusted R^2	0.011	0.029	0.027	0.067	0.002	0.018	0.018	0.023	-0.003	0.021	0.021	0.060

Panel B	DG$_{t+1}$											
	United States				**United Kingdom**				**France**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DP$_t$	-0.00	-0.00	-0.00	0.00	-0.02*	-0.02*	-0.02	-0.03	-0.04***	-0.04***	-0.04**	-0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Recession$_t$		-0.00**	-0.01	-0.02		-0.01	-0.00	0.05		-0.01	-0.03	0.03
		(0.00)	(0.04)	(0.04)		(0.00)	(0.07)	(0.07)		(0.01)	(0.08)	(0.09)
D/P$_t$ ×			-0.00	-0.00			0.00	0.02			-0.01	0.01
Recession$_t$			(0.01)	(0.01)			(0.02)	(0.02)			(0.02)	(0.02)
Term$_t$				-0.00				0.00				0.00
				(0.00)				(0.00)				(0.00)
Inflation$_t$				0.10*				0.22*				0.43
				(0.05)				(0.12)				(0.28)
Oil$_t$				-0.00				-0.18***				-0.44***
				(0.01)				(0.02)				(0.12)
Constant	-0.00	-0.00	0.00	0.02	-0.07*	-0.07*	-0.07	-0.11	-0.15***	-0.14***	-0.13**	-0.16**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)	(0.06)	(0.07)	(0.04)	(0.04)	(0.05)	(0.07)
Observations	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.001	0.032	0.033	0.040	0.023	0.030	0.030	0.110	0.044	0.048	0.049	0.153
Adjusted R^2	-0.002	0.026	0.023	0.022	0.020	0.024	0.021	0.093	0.041	0.042	0.039	0.136

Appendix D, Table 1: OLS Regression results of return and dividend growth against dividend yield, recession dummy using OECD G7 indicator, an interaction term between the dividend yield and recession dummy, term spread, inflation and oil price uncertainty for the countries the United States, the United Kingdom, and France. Sample period of June 1995 – September 2022.

Note: Newey-West (1987) standard errors with 5 lags in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel A	Return$_{t+1}$															
	Large Growth				**Large Value**				**Small Growth**				**Small Value**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DP$_t$	0.02*	0.02*	0.02	0.01	0.00	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Recession$_t$		-0.02	0.02	-0.04		-0.03	0.07	-0.06		-0.00	0.10	-0.05		0.00	0.05	-0.03
		(0.02)	(0.15)	(0.13)		(0.02)	(0.26)	(0.25)		(0.02)	(0.16)	(0.16)		(0.03)	(0.34)	(0.33)
D/P$_t$ ×			0.01	-0.00			0.03	-0.01			0.02	-0.01			0.01	-0.00
Recession$_t$			(0.03)	(0.03)			(0.07)	(0.07)			(0.03)	(0.03)			(0.09)	(0.08)
Term$_t$				-0.00				0.00				0.00				0.00
				(0.00)				(0.00)				(0.00)				(0.01)
Inflation$_t$				-0.63**				-0.51**				-0.65***				-0.60**
				(0.25)				(0.24)				(0.21)				(0.29)
Oil$_t$				0.19***				0.13				0.17				0.18
				(0.07)				(0.10)				(0.11)				(0.12)
Constant	0.09*	0.10**	0.09*	0.07	0.01	0.07	0.05	0.08	0.03	0.03	0.02	0.02	0.01	0.01	0.00	0.04
	(0.05)	(0.04)	(0.05)	(0.06)	(0.10)	(0.07)	(0.06)	(0.06)	(0.04)	(0.04)	(0.04)	(0.05)	(0.07)	(0.05)	(0.04)	(0.05)
Observations	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.016	0.021	0.021	0.061	0.000	0.011	0.013	0.043	0.002	0.002	0.005	0.040	0.000	0.000	0.000	0.031
Adjusted R^2	0.012	0.014	0.012	0.042	-0.003	0.005	0.003	0.024	-0.002	-0.005	-0.005	0.021	-0.003	-0.006	-0.009	0.012

Panel B	DG$_{t+1}$															
	Large Growth				**Large Value**				**Small Growth**				**Small Value**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DP$_t$	0.00	0.01	0.01	0.01	-0.03***	-0.03***	-0.03***	-0.04***	-0.00	-0.00	-0.00	-0.00	-0.02***	-0.02***	-0.02***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Recession$_t$		-0.02***	-0.02	-0.04		-0.01	-0.04	0.02		-0.00	0.01	0.02		-0.01	-0.04	0.07
		(0.01)	(0.05)	(0.05)		(0.01)	(0.05)	(0.05)		(0.01)	(0.09)	(0.11)		(0.01)	(0.05)	(0.06)
D/P$_t$ ×			-0.00	-0.00			-0.01	0.01			0.00	0.01			-0.01	0.02
Recession$_t$			(0.01)	(0.01)			(0.01)	(0.01)			(0.02)	(0.02)			(0.01)	(0.01)
Term$_t$				0.01*				-0.00				0.01**				-0.01
				(0.00)				(0.00)				(0.00)				(0.01)
Inflation$_t$				0.72*				0.24*				0.41				0.72***
				(0.41)				(0.13)				(0.26)				(0.18)
Oil$_t$				0.03				0.00				0.01				-0.06**
				(0.04)				(0.02)				(0.07)				(0.03)
Constant	0.03	0.04	0.04	0.04	-0.12***	-0.10***	-0.09***	-0.12***	0.00	0.00	0.00	-0.02	-0.09***	-0.08***	-0.08***	-0.13***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
Observations	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.003	0.025	0.025	0.098	0.172	0.183	0.185	0.252	0.000	0.001	0.001	0.035	0.076	0.078	0.079	0.233
Adjusted R^2	-0.000	0.018	0.015	0.081	0.169	0.178	0.177	0.237	-0.003	-0.006	-0.009	0.016	0.073	0.072	0.070	0.218

Appendix D, Table 2: OLS Regression results of return and dividend growth against dividend yield, recession dummy using NBER indicator, an interaction term between the dividend yield and recession dummy, term spread, inflation and oil price uncertainty for the indexes S&P500 Pure Growth, S&P500 Pure Value, S&P600 Pure Growth, and S&P600 Pure Value representing the equity cross-sections Large Growth, Large Value, Small Growth, and Small Value. Sample period of June 1995 – September 2022.

Note: Newey-West (1987) standard errors with 5 lags in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$