The Predictive Power of the Term Spread and Financial Variables for Economic Activity across Countries

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Abstract: In recent years, there has been renewed interest in the moments of the yield curve (or alternatively, the term spread) as a predictor of future economic activity, defined as either recessions, or industrial production growth. In this paper, we re-examine the evidence for this predictor for the United States, other high-income countries, as well as selected emerging market economies (Brazil, India, China, South Africa and South Korea), over the 1995-2023 period. We examine the sensitivity of the results to the addition of financial variables that measure other dimensions of financial conditions both domestically and internationally. Specifically, we account for financial conditions indexes (Arrigoni, et al., 2022), the debt service ratio (Borio, et al., 2020), and foreign term spreads (Ahmed and Chinn, 2023). We find that foreign term spreads and the debt service ratio in many cases yield substantially better predictive power, in terms of in-sample fit using proportion of variance explained. Overall, the predictive power of the yield curve, as well as other financial variables, varies across countries, with particularly little explanatory power in emerging market economies.

Key words: yield curve, term premium, expectations hypothesis of the term premium, industrial production, recession

JEL classification: C22, E37, E43

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1. Introduction

Over the past recent years, various observers have pointed to yield curve inversions as predictors of recessions or economic downturns. The 2020 recession was preceded by a yield curve inversion, although that is now typically viewed as a happenstance, given the pandemic would've induced a recession regardless of the underlying conditions of the economy. In 2022, the yield curve again inverted. While the inverted yield curve is commonly seen as one of the best predictors of recession in the United States, the same is not true for other countries. And even in the United States, doubts have been raised about the relevance of the yield curve as an early warning signal, after the implementation of unconventional monetary policies. Figure 1 displays the yield spread, the difference between long (10 years) and short term (3 months) government interest rates, through time for the United States, selected European countries, and Japan. The yield spread dips before each recession period and turns negative for all but one, including the recession beginning in 2008. For European countries, the relationship is not as consistent but there does appear to be some level of coincidence.

The motivation for studying the yield spread is manifold. First, policy makers often need to make decisions today, based on expectations regarding future economic conditions. Although policymakers rely on a range of data and methods in forecasting future conditions, movements in the yield curve have in the past proved useful, and could still represent a useful additional tool.

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Second, variations in the correlations between asset prices and economic activity might inform debates regarding the workings of the macroeconomy. The fact that it works for some countries, and not others, might be suggestive of certain channels being important, to the exclusion of others. A similar sort of reasoning applies to examining the goodness of fit over different time periods.

While there is already a voluminous literature on the subject of yield curves and US economic activity, we nonetheless believe now is an opportune time to re-examine the evidence. This conviction is rooted in two developments.

The first is the advent of unconventional monetary policies – including quantitative and credit easing, as well as forward guidance – which might have altered the information contained in spreads.

The second revolves around the greater prominence of international factors – such as foreign actors like central banks, and potentially tighter linkages of international bond yields – in affecting the informational content of spreads.¹

The final motivation is driven by the development of newer financial indicators that allows for evaluating the relative informational content of term spreads: financial conditions indices, debt service ratios, foreign term spreads.

¹ See for instance Warnock and Warnock (2006). A contrasting view is in Rudebusch et al. (2006) and Wu (2008).

The paper is organized in the following fashion. In section 2, we lay out a framework for examining what determines the long term interest rate relative to the short, and relate that to the extant literature on the yield curve as a predictor of recessions and economic activity, as well as the role for additional financial factors. In section 3, we describe the data and the empirical tests we implement for predicting recessions in high income economies. In Section 4, we repeat the exercise, but using as a dependent variable industrial production growth. Section 5 considers emerging markets. Section 6 concludes.

2. Background

2.1 Theoretical Framework

Following previous literature, this paper focuses on the yield spread defined as the 10year government bond yield less the 3 month treasury yield (or closest equivalent for countries other than the United States)².

The linkage between the long-term and short-term interest rates can be decomposed thus:

² Using aggregate Euro area data, Moneta (2003) found that the 10-year/3-month spread specification performed better than any other pair of yield maturities that included two of the following: 3-month, 1-year, 2-year, 5-year, 10-year.

$$i_t^n = \frac{(i_t + i_{t+1}^e + \dots + i_{t+n-1}^e)}{n} + l_t^n \quad , \tag{1}$$

where i_t^n is the interest rate on a bond of maturity n at time t, i_{t+j}^e is the expected interest rate on a one period bond for period t + j, based on information available at time t, and l_t^n is the liquidity (or term) premium for the n-period bond at time t. This specification nests the expectations hypothesis of the term structure (EHTS) (corresponding to the first term on the right hand side of equation 1), and the liquidity premium theory (corresponding to the second term).

The EHTS merely posits that the yield on a long-term bond is the average of the one period interest rates expected over the lifetime of the long bond. The liquidity premium theory allows that there will be supply and demand conditions that pertain specifically to bonds of that maturity. The presence of idiosyncratic effects associated with a certain maturity of bond is sometimes linked to the "preferred habitat theory", the idea that certain investors have a preference for purchasing assets of specific maturities. Since $l_t^n > 0$ and is expected to rise as n becomes large, the yield curve will slope upward when short rates are expected to be constant over time. The term spread is given by:

$$spread_t = i_t^n - i_t$$
 (2)

For the sake of simplicity, we consider the case where $l_t^n = 0$ (i.e., the EHTS explains all variation in long rates). Suppose further expected short rates are lower than

the short rate today. Then the long rate will be lower than the short rate (i.e., the yield curve inverts). Since low interest rates are typically associated with decreased economic activity, an inverted yield curve should imply an expected downturn, especially given that $l_t^n > 0$, then an inversion should imply a downturn *a fortiori*.³

Why should short interest rates be lower during an economic downturn? The reasoning follows two – not necessarily mutually exclusive -- avenues. The first is that decreased economic activity decreases private sector demand for credit; at the same time the monetary authority is likely to have decreased the policy rate in response to the slowdown, as in the Taylor Rule. The second is that the monetary authorities raise rates that precipitate the subsequent slowdown.

2.2. Selective Literature Review

The literature on the usefulness of the yield spread in forecasting future growth is extensive and we review only a subset of the analyses here. Some early studies regarding the relationship between growth and the yield spread date to the late 1980s; Harvey (1988, 1989), Stock and Watson (1989), Nai-Fu Chen (1991), Estrella and Hardouvelis (1991) among others, suggested that an inverted yield curve (in this case a negative yield spread) could signal an impending recession. These early studies were

³ Minoiu, Schneider and Wei (2023) propose a different channel for the spread predicting future economic activity. A steepening curve increases bank profitability and hence bank lending, thereby spurring growth.

primarily conducted using U.S. financial data to predict future Gross Domestic Product (GDP) growth.

Some subsequent research focused on whether the relationship between the yield spread and future economic growth held up in countries other than the United States. Harvey (1991), Davis and Henry (1994), Plosser and Rouwenhorst (1994), Bonser-Neal and Morley (1997), Kozicki (1997), Estrella and Mishkin (1997) and Estrella, Rodrigues and Schich (2003) studied non-US OECD countries using post-1970 data, and generally conclude that the yield spread can be used to some extent in predicting future economic growth. However out-of-sample studies conducted by Davis and Fagan (1997) and Smets and Tsatsaronis (1997) using, respectively, U.S. and German data, and European data, found that parameter estimates are unstable over time. Moreover, the estimated regressions exhibited poor forecasting capabilities. Haubrich (2020) reviews some of these large country analyses.

More recently, Sabes and Sahuc (2023) find the term spread predicted recessions in the euro area, Germany, France, Italy and Spain. Other studies of a crosscountry nature have relied upon panel analyses. These include Gebka and Wohar (2018) or Borio, Drehman and Xia (2018), or Hasse and Lajaunie (2022) (the latter for short horizon, including a lagged dependent variable).

Several of the recent analyses incorporate additional financial variables. Hence, while the simplest model is a single-variable specification with the yield spread as the lone independent variable, some subsequent research allows for additional variables, such as the short term policy rate -- at least when predicting recessions (as opposed to growth). One prominent example of this approach is Wright (2006). In his paper, Wright argues that adding the short-term rate strengthens the in-sample forecasting results when using a probit model to predict recessions.

Other financial variables that have been considered in addition to, or instead of, the term spread include financial conditions index (Arrigoni, et al., 2022; Adrian et al., 2019; Hatzius, et al., 2010), the financial cycle proxy and the debt-service ratio (Borio et al., 2020), alternatively weighted stock market variables (Chatelais, et al., 2023), and foreign term spread (Ahmed and Chinn, 2023).

3. Predicting Recessions

3.1 Data and models

Our first focus is on the developed countries that have historically been examined, including the US and Canada, large European countries, and Japan, over the 1995-2022 period. These are also countries where the interest rates represent marketdetermined rates in liquid financial markets. While it would be desirable to have as long a sample period as possible in order to maximize the number of recessions encompassed, the sample period we used is constrained by the availability of all the variables we use. We also subsequently expand our analysis to encompass some emerging market countries – Brazil, India, China, South Africa and South Korea – which further shortens the sample period.

We examine recessions (peak-to-trough) as determined by the NBER Business Cycle Dating Committee (for the US) or the Economic Cycle Research Institute (ECRI), which uses a similar methodology to that of the NBER. Note that in our examination of recessions, we do not take a stand on any recessions occurring past 2022M12, given that it's possible that some countries – particularly euro area countries – entered into recession in 2023.

Following the literature, the models we use are of this following form:

$$Pr(R_{t+k} = 1) = \varphi(\beta_0 + \beta_1 Spread_t + \beta_2 3mo_t + X_t \Gamma), \tag{3}$$

where t is the current time period, k is the forecast horizon and $\varphi(.)$ denotes the standard normal cumulative distribution function, and X is a vector of variables including the financial conditions index, the debt service ratio and foreign term spread. We start by looking at results for the standard horizon of interest, that is k=12 months.

3.2 Benchmark results

We first focus on the yield curve, in particular the first two parameters, namely the level and slope of the curve. For instance, while multiple studies find the yield curve alone is a useful predictor of recessions when using aggregate Euro area data, Wright (2006) argued there is no reason to believe that an increase in the short-term interest rate should have the same consequence as a decrease in the long term rate. Hence Tables 1 and 2 display the results from the probit model estimates for each country without and with the short rate for k=12 months. One remarkable point is that the spread and spread plus short rate is most successful at predicting recessions for the US (excepting Canada), according to the Pseudo-R² statistic (which does not penalize for increased model size). This result mirrors those found in Chinn and Kucko (2015).

The spread also predicts recessions in Germany and France, although the goodness-of-fit is only about half of that for the US and Canada.⁴ Generally, the models that also include the short-term interest rate outperform those that only include the yield spread, with the exception of Sweden.

Interestingly, results for the remaining countries are starkly different. The spread and short rate are essentially unimportant for determining UK recessions. In two countries – Italy and Japan – the spread has the wrong sign, and significantly so. A different explanation has to be forwarded for this correlation. For Italy, one could point to sovereign risk. For Japan, one might conjecture that the country's extended experience with the zero lower bound has resulted in term spreads signaling different behavior than in the other economies.⁵

⁴ The motivation for predictive power for the term spread relies on a central bank reaction function that responds to output and inflation gaps. To the extent the ECB policy rate is adjusted to the euro area-wide – rather than country specific – gaps, one would expect the predictive power of the country specific term spread to be attenuated. For discussion of how one rule does not simultaneously fit all member country conditions, see Papadamou et al. (2018).

⁵ Chinn and Kucko (2015) and Ishii (2022) obtain similar results for Japanese recessions.

3.3 Adding financial variables

Hatzius et al. (2010) show that the financial conditions index (FCI hereafter) has a marginal predictive power for economic activity, controlling for lagged activity. As suggested in Plagborg-Møller et al. (2020), the horizon at which financial conditions affect GDP is relatively low (see also Ferrara et al., 2022). Adrian et al. (2019) and Arrigoni et al. (2022) argue that there is a nonlinear relationship between FCIs and growth, particularly for those episodes relating to financial crises. They both use quantile regression to show that the impact of FCIs is stronger in the left tail of the distribution of growth. In order to investigate the role of the FCI, we augment the spread plus short rate with this variable. The results are shown in Table 3, where the FCI is defined as lower values representing more stressed conditions.

For the US and Canada, the FCI enters in with expected sign: a higher value of FCI reduces the probability of recession, with statistical significance. In all other instances, the FCI coefficient is either not significant (France, Japan, UK), or has the wrong sign, with statistical significance (Germany, Sweden).

We now consider a variable with a different cyclical behavior than standard financial variables, namely the debt-service ratio for nonfinancial firms. This variable is related to the financial cycle variables first described by Borio (2014). Borio, Drehmann and Xia (2020) examine both aggregate financial cycle variables, as well as the debtservice ratio, focusing on panel results. We utilize the debt-service ratio compiled by

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Borio et al. (2020) and updated by the BIS, interpolated to monthly frequency.⁶ The results of augmenting the terms spread/short rate/FCI model with the debt service ratio are reported In Table 4.

The first thing to note is that the goodness of fit statistics improves substantially in those cases where the debt-service ratio coefficient enters with statistical significance. This point is strongest for the US where the Pseudo-R² more than doubles to 0.54. For Italy and the UK, goodness of fit also increases substantially; for the latter, it appears that the ratio is the only important determinant of recession probabilities. The ratio is also important in the German and French cases (borderline significance in the latter case).

Finally, we add the foreign term spread, calculated as the GDP weighted average of US, euro area, UK, and Japanese interest rate spreads, as a regressor, following Ahmed and Chinn (2023). As shown in Table 5, for this sample period (1995-2023), the foreign term spread is more statistically important than the US term spread, even after inclusion of the FCI and the debt service ratio.

Interestingly, the finding of an important role is not restricted to the United States. For Canada, France, and Sweden, the foreign term spread is not only influential

⁶ The quarterly series are interpolated to monthly using a one-sided process that forces the quarter's last month value to match the quarterly value. This procedure ensures that the interpolated series does not incorporate future information.

(with statistical significance), in the latter case is the only variable that is statistically significant in the full specification. To the extent that Sweden constitutes the quintessential small open economy, this is perhaps unsurprising.

3.4 Assessing the gain from financial variables

A first approach the assess the gain from those financial variables is to look at estimated recession probabilities. Figure 2 depicts the predicted 12-month-ahead recession probabilities for each country using a baseline (spread and short rate) specification, and the full specification including all financial regressors.

Turning to the familiar case of the United States, we replicate several outstanding findings. The term spread model (with short rate) catches the 2001 and 2008-09 recessions using a 40% threshold, while missing the 2020 Covid recession. However, the full specification is even more successful, indicating a prediction of the first two recessions using a 50% threshold, with no false positives apparent. Taken literally, the results suggest that had no pandemic occurred, the US would have avoided a recession in 2020.

The Canadian term spread has similar predictive power to that of the US. That being said, there are only two recessions covered in the sample period. One has to use a relatively low threshold (20%) to predict the two recessions, and in addition, there is a false positive in 2001. On the other hand, the fully specification, using a 50% threshold, captures both recessions.

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The term spread plus short rate possesses some predictive power in France and Germany. That being said, the French model catches two of three recessions using a 20% threshold, while providing a false positive in 1996. A 40% threshold for Germany catches two of three recessions, but also predicts a recession 1996. The full specification in some sense provides more satisfactory results, insofar as two of three recessions are predicted using a 40% threshold in both countries (missing the 2020 recession). On the other hand, for Germany, a false positive is signaled for 1999-2000.

Italy, Japan and the UK are three countries for which the probit regressions indicated little explanatory power for the term spread. While the term spread coefficient is statistically significant for the first two, the sign is opposite the conventionally expected. For Japan, term spreads have some predicted power through 2008, but not thereafter. In the UK, a threshold of 0.25 would predict two of three recessions, but provide two false positives, for 2002, 2004.

In contrast, for Italy and the UK, the full specification does substantially better, with recession probabilities matching up with recession dates much better (although there is a false positive for 2010 Italy, and the 2020 UK recession is missed). In no case can we identify a reasonable specification for Japan.

The term spread does not explain a high proportion of variation for Sweden, but using a 25% threshold captures both recessions, while providing a false positive in 2001. The full specification using a 50% threshold similarly captures both recessions, but signals a (non-existent) recession in 2017. Overall, the results indicate that the usefulness of the term spread (and short rate) variable varies between countries, with the US and Canada being perhaps the most prominent examples. In all cases but Japan, the full specification provides higher probabilities of recession when those recessions occur.

A useful comparison of models with binary outcomes can be done through the so-called Receiver Operator Characteristic (ROC), also referred to as the "area under the curve" (AUC), see for example recent applications in Ferrari Minesso et al. (2023) or Vrontos etal. (2023). The ROC curve is obtained by plotting the share of model's correct predictions (the true positive rate) vs the share of model's incorrect predictions (the false positive rate), for various thresholds. The idea is to assess the distance of this curve with respect to the 45-degree line that corresponds to the ROC value for a model with random assignment. This AUC measure allows an evaluation of the quality of the model for all the thresholds: the higher the AUC, the better the quality of the model.

Figures 3a and 3b present the AUC measures for the 8 countries in the panel. Previous results are stressed out by those graphs. We note that the model with all variables largely improve other models, especially for UK, US, Sweden and Italy. It is noteworthy that the DSR and foreign spread variables lead to a strong improvement in the goodness of fit according to AUC measures. The quality of the model for Japan is especially low, as already mentioned. We also note that specifications with only term spread and term spread and short rate provide similar AUC measures.

3.4 Checking other horizons

Previous results have been obtained for a given horizon of k=12 months, which is the standard horizon in this literature. This stems from the fact that the US spread has been shown to have on average a yearly lead with respect to US recessions. However, when assessing the role of other financial variables and other countries, we can question this assumption. In this respect, for each financial variable we run Probit models at various horizons from k=1 to k=24 months, as well as for the complete model with all variables. We retain Pseudo- R² as a measure of the goodness of fit of the models for each horizon k, as can be seen in Figure 4 (for the US). We first note that the optimal lead (i.e. the one that maximizes the Pseudo- R^2) for the spread and the 3-month interest rate is rather long, close to 1.5 years. In contrast, the FCI possesses a very short lead of one month, in line with the recent literature (see Plagborg-Moller et al., 2020, Ferrara et al., 2022). The DSR and the foreign term spread have an intermediate behavior, with respectively an optimal lead of k=9 and k=6 months, associated with a strong Pseudo-R² of about 0.40. Interestingly, the complete model with all variables shows an optimal lead of k=6months and a very strong Pseudo- R² of 0.80. Among other countries (results not reported here), Canada is extremely similar to the US, with an optimal lead of k=6months (Pseudo- R² of 0.84). Results are less striking for other countries, but we get that the Pseudo- R² at *k*=6 months is generally much higher than at *k*=12 months, except for the UK.

This is the reason why we decided to also run Probit models for a horizon of *k=6* months for all countries (see Table 5b). Results confirm that DSR and foreign term spread play an important role in the anticipation of recessions also at 6 months. The model for Canada appears interesting as all variables being significant, except that the term spread has the wrong sign. The term spread is still significant at six months for France, Germany and Sweden.

4. Predicting Growth

In this section, we focus on economic growth, and we check if the previous financial variables are also able to predict changes in economic activity.

4.1 Pre-pandemic In-Sample Results

As we are dealing with monthly frequency variables, we focus on industrial production as measure of economic activity. While GDP is the broadest indicator of economic activity, the use of industrial production presents some substantial advantages in terms of timeliness and reliability.⁷ In any case, growth rates of industrial production tend to follow GDP closely⁸. All of the countries in our panel report industrial production at a

⁷ By reliability, we mean that the industrial production series do not get revised as significantly as GDP.

⁸ For instance, the correlation between GDP and IP growth in the US and UK are .76 and .72 respectively.

monthly frequency while GDP is only reported at a quarterly frequency; using IP therefore affords us a larger data set.

We start with a simple bivariate model:

$$IPGrowth_{t,t+k} = \beta_0 + \beta_1 Spread_t + X_t \Gamma + \varepsilon_{t+k} , \qquad (4)$$

where $IPGrowth_{t,t+k}$ is the annualized growth rate over the period t through t+k, and the other variables are as in the previous section.

In words, the yield spread at time *t* predicts the annual growth rate of industrial production from time *t* to time period t + k months. We examine this model with k = 12 (i.e. growth over a one year time horizon). Since adjacent year over year growth figures will be drawing from overlapping data points, the resulting error terms will be serially correlated. To account for this serial correlation, we conduct our statistical inferences using heteroscedasticity and serial correlation robust standard errors. ⁹ We restrict our analysis to 1995-2019 in order to avoid data encompassing the pandemic. If we believe the onset of the pandemic and associated public health measures were largely a surprise, we would not anticipate market expectations to incorporate the severity of the downturn.

⁹ We have investigated whether the variables are stationary or not. Unit root tests indicate that the spreads and industrial production changes are stationary.

We turn first to the results from the model using basic specifications with term spread and term spread and short rate (Tables 6-7). Except for Italy and the UK, the term spread shows up with a significant and positive coefficient in at least one case. Germany, in fact, exhibits behavior closer to the canonical view, with a higher spread presaging faster growth, and a higher short rate reducing growth, and a goodness of fit at 0.37. Each one percentage point increase in the spread is associated with a percentage point increase in growth, and each one percentage point increase in the short rate is associated with a percentage point decrease in growth. Swedish growth is also well explained; a one percentage point increase in spread is associated with a 4.4 percent jump in growth. Figure 5 displays the actual IP growth (black line) and predictions from the spread plus short rate regression (green line). This is compared against an AR(1) prediction (tan line). Notice the dates indicate the start of the 12 month period of growth.

For Canada, Germany, and Japan, and the US, the spread is a statistically significant determinant of growth, although the proportion of variation explained is fairly low – below 13% and particularly low for the US. While it's typically thought that the predictive power of the spread has declined in recent times, it is interesting to note that the spread is more statistically significant than it was in Chinn and Kucko (2015) period of 1998-2013 for Canada and France.

The debt-service ratio is statistically significant for France, Italy, the UK, US and (at the 10% level) Sweden, with the coefficient in the expected direction. A one

percentage point increase in the debt service ratio decreases growth by 0.6 to 2.7 percentage points. The largest impact is for Italy. On the other hand, the debt-service ratio has the unanticipated sign (and significantly so) for Canada and Germany.

Finally, adding the foreign term spread provides some interesting results. We replicate Ahmed and Chinn's (2023) finding that the foreign term spread well predicts US growth, and indeed does so more robustly than the US term spread. A one percentage point increase in the foreign term spread implies accelerated growth of 5.5 percentage points, with the US term spread going the opposite direction (by 2.4 percentage points). For Canada and France, the foreign term spread is again statistically significant. Figure 5 depicts the in-sample prediction from the full specification as a red line.

4.2 Out-of-Sample results

A common critique of in-sample estimation is that the model estimates the fitted values using data that would not have been available at the time of the observation being fitted. The results of an in-sample forecast will be using extra information to fit the parameters to the data and could therefore overstate the predictive power of the independent variable. If we were to attempt to forecast growth from today to one year into the future, we would not be privy to the information in the interim.

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One way to circumvent this potential problem is by conducting a pseudo out-ofsample regression analysis. Each yield spread observation is used to predict future growth with truncated data such that the only data used is data that existed prior to the observation. For example, if we have a data set that ranges from 1995-2019 for yield spreads and other financial variables and we want to predict industrial production growth from January 2020 to December 2022, we could restrict our regression to only use data from 1995-2019 in calculating the constant and slope parameters for our estimation of 2020 growth. Then, to estimate IP growth from February 2020 to February 2021, we re-run the regressions adding the January 2020 data and use the newly generated parameter estimates to predict growth over that time period.

The parameter estimates from the rolling regressions are used to generate a series of fitted values for year-over-year growth for each country. We opt to compare the root mean square forecast error (RMSFE) criterion, and compare against a naïve RMSFE. In this case, our naïve forecast is a simple AR1 model of growth.

Given the extreme variation in growth over the pandemic period, it's unsurprising that the conventional out-of-sample exercise is not useful for discerning model fit. No model does well over the immediate pandemic period, so evaluation over the period encompassing the 2020M02-M04 recession (in the US) doesn't make sense. On the other hand, evaluating over the 18 months up to the last observation of industrial production in December 2022 (i.e., growth for period starting in December 2021), when the effects of the drop and subsequent rebound are excluded might be more informative.

The mean error and RMSFE from the specifications estimated pre-pandemic, and applied to the last 18 months are shown in Table 11, for the AR(1) specification, the spread plus short rate, and the full specification. There are few striking findings. The naïve AR(1) provides the smallest RMSFE in only one case (Sweden). The baseline model provides the smallest RMSFE for France and Japan, even though in the latter case we know that specification does miserably in-sample. The full specification, including the DSR and foreign term spread, does noticeably better than naïve or baseline only in the case of the US.

5. Emerging Markets

We selected five major emerging market economies to examine for business cycle predictors: Brazil, India, China, South Africa and Korea. The analysis was complicated by the brevity or absence of data for some (short sample of long rates for India, no financial conditions index for South Africa, no debt service ratio for Brazil). In addition, for some countries, recessions were such a common occurrence that no variables correlated with the recessions (seven recessions in Brazil), or at the opposite end, only one (2020) recession for China. Consequently, we focus our attention on predicting industrial production growth, in the pre-pandemic period. In general, the term spread and short rates are typically able to explain only a small proportion of variation. For China, India, and Korea, we are able to explain some variation in growth, but have essentially no success in Brazil and South Africa. Table 12 shows the best estimates for the countries for which we obtain somewhat plausible estimates.¹⁰

For India, the term spread points in the unanticipated direction, while the short rate has the anticipated sign. The foreign term spread on the other hand has the correct sign insofar as a steepening curve associated with more rapid foreign growth signals faster Indian growth. The top panel of Figure 6 displays the in-sample results for India.

Why the unanticipated sign for the spread? The typically expected sign relies on the short and long rate default risk premia being the same. For Indian government bonds (currently rated BBB- and Baa3 by S&P and Moody's respectively), this assumption seems inappropriate.¹¹

¹⁰ Mehl (2009) finds 5 year-3 month spreads predict growth (in the expected direction) for Brazil and South Africa, but negatively correlated for India and Korea, at the one year horizon. For all the emerging market economies we examine (save China), the US or euro area spread also predicts growth (Mehl does not cover China). The sample ends in 2005, so the sample periods are shorter and largely precede the samples we use.

¹¹ 5 year CDS's on Indian government bonds dropped dramatically in mid-2017, when Moody's rating rose from Baa3 to Baa2.

We are able to explain a much larger proportion of variation in Chinese industrial production growth (adjusted R^2 of 0.73) despite some issues with seasonality. The coefficient of 3.1 indicates that each one percentage point increase in 10yr-3mo spread is associated with a 3.1 percentage point faster industrial production growth – a figure comparable to that for Germany.¹² The financial conditions index, the debt-service ratio and the foreign term spread all have the anticipated signs. The only coefficient that does not have the expected sign is the short rate. A one percentage point increase in the short rate is associated with a 3.6 percentage point *faster* industrial production growth rate over the next 12 months. This result is obtained regardless of what other variables are included in the regression, so seems robust. The middle panel of Figure 8 shows the fitted values; excepting the depth of the 2008 recession, industrial production growth is well-tracked.

Finally, as indicated in column 3 of Table 12, the Korean short rate enters significantly with the expected sign, in a specification with adjusted R² of 0.25. The term spread also has expected sign but is not significant. The financial conditions index has a negative, significant, sign. Rearrangement of the variables does not alter the basic result that the FCI has a negative sign. That specification's fit is shown in Panel 3 of Figure 6. A

¹² This result contrasts with Sowmya and Prasanna (2018) who find a negative relationship between slope and subsequent output. Interestingly, Jiang, Guo and Zhang (2017) don't find the spread as a useful predictors for GDP growth 2000-2016.

specification including only the Korean and Japanese (not foreign) term spreads explains 18% of the variation in IP growth.

6. Conclusion

This paper has explored the importance of the yield spread in forecasting recessions and future industrial production growth. Generally speaking, in-sample results suggest the yield spread is indeed important and has significant predictive power when both recessions and growth over one-year time horizon are considered, even in a recent period where the conventional wisdom holds for decreased explanatory power (e.g., Chinn and Kucko, 2015).

Interestingly, the spread is not a particularly reliable predictor of industrial production growth over the sample period. This is in line with Chinn and Kucko's finding that relative to the 1970-1997 period, spreads were less predictive of IP growth. Nonetheless, a higher spread is associated with a lower probability of recession.

Contrary to speculation in Chinn and Kucko, the spread (along with short rate) remains a significant predictor of US recessions and growth, despite the extended adoption of a zero interest rate policy (ZIRP). That finding does not detract from the fact that other financial variables prove to be important for the US (and sometimes, more important, as is the case for the foreign term spread). We also find that adding financial variables like the foreign term spread and the debt service ratio often leads to a strong improvement in the goodness-of-fit of models as measured by the Pseudo-R² or the area under the ROC curve (AUC). Especially, models for Canada and the US turn out to be extremely good at both horizons of 6 and 12 months.

The results we obtained in the out-of-sample forecasting exercises were less informative regarding the reliability of the models. To the extent that market participants did not ascribe any measurable probability to a public health emergency of the magnitude experienced, it seems a comparison of out-of-sample fit is inappropriate. In terms of assessing whether the *post-lockdown period* was explainable by financial variables, it's not clear that they are able to track industrial production growth.

We tried to expand the set of countries examined to include some emerging markets. In general recessions as defined by a methodology similar to that adopted by the NBER were not well predicted in Brazil, India, China, South Africa and Korea. Industrial production growth was predictable to a limited degree in India, China and Korea, although the set of financial variables that were relevant differed between each country. Hence, we conclude that extrapolation to the stylized facts we find in high income economies to emerging market economies is unwise.

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Data Appendix

The interest rate data are drawn from OECD.

- The US ten year series is the constant maturity series from the Treasury, while the three month yield is the Treasury yield in the secondary market.
- The Chinese ten year government yield is from investing.com
- The Brazilian interest rates are from IMF, IFS.

Recession indicator variable (peak-to-trough):

- For US is from the NBER.
- For all other countries, the baseline indicator is drawn from Economic Cycle Research Institute (ECRI).

Industrial production data comes from OECD Main Economic Indicators.

• The Chinese year-on-year industrial production growth is drawn from OECD.

Financial Conditions Index (Araggoni et al., 2022). Personal communication from Fabrizio Venditti.

Foreign Term Spread (FTS) is the GDP weighted average of US, Canada, Euro area, Japan, UK, 10 year – 3 month spread.

- The FTS is country specific when the country is the US, Canada, France, Germany, Italy or Japan.
- The FTS is the GDP weighted average of spreads for Sweden, Brazil, India, China, South Africa, and Korea.

Debt-Service Ratio in % is from Bank for International Settlements for 1999-2022. For 1985-98, personal communication from Dora Fan Xia.

coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	-0.679	-0.652	-0.601	-1.285	-1.012	-0.770	-1.119	-0.481
	0.159	0.184	0.123	0.149	0.132	0.181	0.097	0.160
spread	-90.079	-59.632	-38.703	27.798	59.202	-58.467	9.069	-72.817
	18.759	15.403	10.408	6.467	10.576	16.424	6.499	13.509
Pseudo R								
sq.	0.217	0.097	0.052	0.056	0.080	0.085	0.007	0.201
Ν	324	324	324	324	324	324	324	324

 Table 1: Recession Twelve months ahead, Spread Only, 1995-2022

Notes: Probit regression coefficients (standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	-0.890	-0.977	-1.156	-1.285	-1.027	-0.599	-1.163	-1.084
	0.270	0.233	0.169	0.216	0.133	0.206	0.196	0.342
spread	-86.763	-55.338	-43.386	27.781	53.862	-60.905	10.425	-55.231
	19.123	15.569	10.436	7.555	11.563	17.243	8.370	15.900
3 mo rate	6.489	12.601	27.871	-0.015	26.471	-8.978	1.104	13.613
	6.592	4.904	4.792	3.488	23.094	5.107	4.307	6.648
Pseudo R								
sq.	0.223	0.131	0.177	0.056	0.083	0.103	0.008	0.222
N	324	324	324	324	324	324	324	324

Table 2: Recession Twelve months ahead, Spread and Short Rate, 1995-2022
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Notes: Probit regression coefficients (standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

-								
coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	0.267	-1.219	-1.546	-0.301	-1.109	-1.231	-1.848	-0.861
	0.415	0.309	0.187	0.308	0.142	0.318	0.505	0.366
spread	-152.406	-44.500	-49.888	-4.089	58.266	-41.028	40.924	-72.026
	30.460	18.599	12.229	10.476	11.857	19.112	16.337	17.775
3 mo rate	-23.207	26.645	43.450	-19.734	46.506	18.586	21.413	12.962
	11.447	7.095	6.060	5.986	26.318	10.088	13.730	7.025
FCI	-2.491	0.049	1.497	-1.446	0.339	0.989	0.079	-0.844
	0.655	0.309	0.299	0.344	0.207	0.407	0.494	0.333
Pseudo R								
sq.	0.357	0.193	0.279	0.119	0.090	0.101	0.051	0.251
Ν	324	264	324	324	324	252	288	324

Table 3: Recession Twelve months ahead, Spread, Short Rate and FCI, 1995-2022

Notes: Probit regression coefficients (standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	3.966	-8.438	-5.928	-10.622	-1.941	16.854	-19.273	-16.753
	2.018	3.860	1.816	1.473	0.535	4.061	3.089	2.610
spread	-168.640	-12.360	-71.579	17.565	38.833	-175.478	92.936	-104.439
	32.927	24.675	16.537	11.095	16.883	43.023	25.994	25.782
3 mo rate	-27.389	50.895	21.821	3.419	22.628	-49.626	81.150	-42.838
	11.481	14.946	10.519	6.508	30.178	21.460	26.237	14.784
FCI	-2.374	-0.060	1.317	1.224	0.261	0.959	4.960	0.770
	0.648	0.305	0.305	0.448	0.213	0.581	1.256	0.561
DSR	-16.214	36.525	40.519	81.506	6.372	-74.757	92.655	109.514
	8.607	19.380	16.651	11.541	3.942	16.697	15.252	18.020
Pseudo R								
sq.	0.379	0.214	0.299	0.290	0.096	0.275	0.406	0.541
Ν	324	264	324	324	324	252	288	324
					•			

Table 4: Recession Twelve months ahead, Spread, Short Rate, FCI, DSR, 1995-2022

Notes: Probit regression coefficients (standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

coefficient	СА	FR	GY	IT	JP	SN	UK	US
constant	0.779	-10.644	-5.712	-19.177	-1.741	8.730	-19.476	-13.196
constant	2.536	4.321	1.884	2.769	0.558	5.364	3.092	3.058
spread	26.868	20.376	-73.823	83.002	44.127	-53.452	84.807	-4.828
-p	56.174	34.049	17.354	20.058	17.315	62.793	33.560	40.183
3 mo rate	-39.804	59.893	23.801	5.514	7.684	-43.229	81.467	26.411
	18.426	16.993	11.528	8.835	32.648	27.094	26.105	25.724
FCI	-6.133	-0.205	1.395	1.143	0.122	-0.712	5.106	1.609
	1.474	0.318	0.356	0.575	0.241	0.871	1.305	0.789
DSR	6.774	48.016	37.897	163.510	6.092	-35.340	93.061	74.397
	11.381	21.801	17.756	23.348	3.933	22.837	14.972	21.796
FTS	-414.775	-29.522	7.501	-195.155	-13.043	-163.385	14.787	-203.747
	91.045	22.152	17.516	29.664	10.684	58.814	38.883	65.902
Pseudo R								
sq.	0.577	0.223	0.300	0.511	0.100	0.327	0.406	0.603
Ν	324	264	324	324	324	252	288	324

 Table 5 - 5a: Recession Twelve months ahead, Spread, Short Rate, FCI, DSR, FTS, 1995-2022

 Table 5 - 5b: Recession Six months ahead, Spread, Short Rate, FCI, DSR, FTS, 1995-2022

coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	-3.46	-2.50	-12.56	-16.36	-2.47	6.59	-18.23	-11.50
	4.57	3.83	2.24	2.52	0.57	5.79	2.96	5.68
spread	484.78	-107.90	-155.95	34.50	-19.59	-159.98	48.97	138.71
	163.17	40.31	25.22	18.94	17.18	73.63	33.53	77.07
3 mo rate	-232.52	19.71	-18.27	-21.44	2.36	-53.52	46.14	72.49
	65.96	15.43	12.21	12.94	33.21	30.76	25.45	32.00
FCI	-23.58	-61.88	0.42	-0.60	-0.06	-1.81	4.31	-1.33
	6.39	35.52	0.34	0.76	0.24	1.03	1.17	1.04
DSR	66.04	8.69	103.22	148.33	14.40	-19.86	91.12	60.21
	26.26	19.35	20.63	21.53	4.01	24.59	15.40	38.61
FTS	-1623.11	47.27	24.65	-175.50	-16.56	-192.75	36.23	-697.22
	434.32	25.23	18.32	28.46	10.71	70.77	40.32	206.66
Pseudo R								
sq.	0.843	0.311	0.369	0.538	0.07	0.478	0.396	0.803
Ν	324	264	324	324	324	252	288	324

Notes: Probit regression coefficients (standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

coefficient	CA	FR	GY	IT	JP	SN	UK
constant	-0.009	-0.023	-0.030	-0.025	-0.010	-0.052	0.010
	0.010	0.016	0.018	0.020	0.014	0.020	0.006
spread	1.513	1.787	3.690	1.087	0.995	4.471	-0.199
	0.452	0.780	1.143	0.801	0.775	1.096	0.455

0.290

288

Table 6: IP Growth next 12 months, Spread Only, 1995-2019

0.127

288

Adj R sq.

Ν

0.113

288

Notes: OLS regression coefficients (Newey-West standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

0.053

288

0.004

288

0.355

288

US 0.008 0.010 0.375

0.433

0.005

288

0.002

288

coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	-0.009	-0.021	-0.008	-0.017	-0.004	-0.043	0.010	-0.029
	0.012	0.014	0.012	0.025	0.012	0.017	0.009	0.014
spread	1.521	1.741	3.719	0.904	2.252	4.422	-0.199	1.500
	0.432	0.725	0.961	0.931	1.127	1.042	0.523	0.527
3 mo rate	0.010	-0.061	-1.012	-0.135	-7.381	-0.328	0.000	0.755
	0.232	0.198	0.413	0.217	4.255	0.260	0.163	0.255
Adj R sq.	0.109	0.125	0.372	0.053	0.086	0.369	-0.001	0.069
Ν	288	288	288	288	288	288	288	288

Notes: OLS regression coefficients (Newey-West standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	-0.015	-0.045	-0.012	-0.056	0.006	-0.062	0.012	-0.033
	0.015	0.019	0.014	0.044	0.015	0.016	0.022	0.014
spread	1.717	2.992	3.870	2.104	1.734	5.329	-0.706	1.860
	0.498	1.039	1.028	1.457	1.130	0.900	0.919	0.494
3 mo rate	0.122	-0.016	-0.882	0.506	-9.349	0.027	-0.014	0.734
	0.315	0.185	0.330	0.529	4.548	0.326	0.538	0.254
FCI	0.017	0.057	0.017	0.047	-0.034	0.071	0.028	0.020
	0.018	0.020	0.020	0.032	0.028	0.019	0.019	0.014
Adj R sq.	0.121	0.373	0.380	0.129	0.109	0.536	0.090	0.095
N	288	228	288	288	288	216	252	288

Table 8: IP Growth next 12 months, Spread, Short Rate, and FCI 1995-2019

Notes: OLS regression coefficients (Newey-West standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

	333 -0.			-			US
		.263 0	. 287 -0				
.059 0.	005 0			.065 0	.082 0	.219 (0.309
	095 0.	.099 0	.099 0	.081 0	.079 0	.051 (0.130
.054 1.	679 2.	.887 1	.303 -0	.707 4	.864 -1	016 2	2.149
.513 0.	880 0.	.709 1	.014 1	769 0	.953 0	.726 (0.545
.332 -1 .	310 -2.	. 105 -0	.395 -12	.355 -0	.585 -0	.506 1	1.813
.322 0.	317 0.	.633 0	.367 6	.209 0	.412 0	.512 (0.481
.014 0 .	059 0.	.011 -0	.029 -0	.044 0	.060 -0	.013 -(0.014
.017 0.	019 0.	.018 0	.024 0	.031 0	.018 0	.018 (0.015
.807 -1.	956 2.	.296 -2	. 671 0	.729 -0	.604 -1	.205 -2	2.364
.232 0.	516 0.	.839 0	.909 0	.603 0	.327 0	.266 (0.913
.185 0.	456 0.	.440 0	.270 0	.135 0	.546 0).348 (0.316
288	228	288	288	288	216	252	288
	332 -1. 322 0. 014 0. 017 0. 807 -1. 232 0. 185 0.	332 -1.310 -2. 322 0.317 0. 014 0.059 0. 017 0.019 0. 807 -1.956 2. 232 0.516 0. 185 0.456 0.	332 -1.310 -2.105 -0. 322 0.317 0.633 0. 014 0.059 0.011 -0. 017 0.019 0.018 0. 807 -1.956 2.296 -2. 232 0.516 0.839 0. 185 0.456 0.440 0.	332 -1.310 -2.105 -0.395 -12 322 0.317 0.633 0.367 6 014 0.059 0.011 -0.029 -0 017 0.019 0.018 0.024 0 807 -1.956 2.296 -2.671 0 232 0.516 0.839 0.909 0 185 0.456 0.440 0.270 0	332 -1.310 -2.105 -0.395 -12.355 -0.325 322 0.317 0.633 0.367 6.209 0.011 014 0.059 0.011 -0.029 -0.044 0.011 017 0.019 0.018 0.024 0.031 0.012 807 -1.956 2.296 -2.671 0.729 -0.012 232 0.516 0.839 0.909 0.603 0.012 185 0.456 0.440 0.270 0.135 0.0135	332 -1.310 -2.105 -0.395 -12.355 -0.585 -0 322 0.317 0.633 0.367 6.209 0.412 0 014 0.059 0.011 -0.029 -0.044 0.060 -0 017 0.019 0.018 0.024 0.031 0.018 0 807 -1.956 2.296 -2.671 0.729 -0.604 -1 232 0.516 0.839 0.909 0.603 0.327 0 185 0.456 0.440 0.270 0.135 0.546 0	332 -1.310 -2.105 -0.395 -12.355 -0.585 -0.506 322 322 0.317 0.633 0.367 6.209 0.412 0.512 0 014 0.059 0.011 -0.029 -0.044 0.060 -0.013 -0 017 0.019 0.018 0.024 0.031 0.018 0.018 0 807 -1.956 2.296 -2.671 0.729 -0.604 -1.205 -2 232 0.516 0.839 0.909 0.603 0.327 0.266 0 185 0.456 0.440 0.270 0.135 0.546 0.348 0

Table 9: IP Growth next 12 months, Spread, Short Rate, FCI, and DSR, 1995-2019

Notes: OLS regression coefficients (Newey-West standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

coefficient	CA	FR	GY	IT	JP	SN	UK	US
constant	-0.258	0.328	-0.320	0.280	-0.112	0.158	0.230	0.117
	0.073	0.094	0.089	0.104	0.088	0.104	0.063	0.079
spread	-0.606	2.133	4.002	1.257	-0.905	3.701	-0.650	-2.429
	0.948	1.065	0.717	1.042	2.038	1.260	0.982	0.786
3 mo rate	0.490	-1.285	-3.380	-0.374	-9.538	-0.859	-0.441	-0.672
	0.332	0.328	0.678	0.373	6.091	0.503	0.515	0.407
FCI	0.039	0.056	-0.029	-0.026	-0.022	0.069	-0.018	-0.006
	0.022	0.019	0.017	0.024	0.029	0.021	0.021	0.009
DSR	0.981	-1.905	3.304	-2.642	0.682	-0.961	-1.256	-0.684
	0.283	0.510	0.802	0.923	0.633	0.468	0.314	0.541
FTS	4.682	-0.698	4.682	0.314	2.062	1.402	-0.546	5.541
	1.770	0.677	1.127	0.957	1.173	1.430	1.022	0.951
Adj R sq.	0.289	0.462	0.542	0.269	0.163	0.549	0.348	0.606
Ν	288	228	288	288	288	216	252	288

Table 10: IP Growth next 12 months, Spread, Short Rate, FCI, DSR, and FTS 1995-2019

Notes: OLS regression coefficients (Newey-West standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

		Canada	France	Germany	Italy	Japan	Sweden	UK	US
AR1	Mean Error	0.033	0.000	-0.012	0.008	0.013	0.012	-0.035	0.031
	RMSE	0.034	0.029	0.056	0.060	0.078	0.038	0.036	0.047
Baseline	Mean Error	0.041	0.028	0.019	0.021	0.000	0.053	-0.031	0.052
	RMSE	0.023	0.022	0.030	0.043	0.044	0.042	0.034	0.022
Full	Mean Error	0.048	0.041	0.005	0.014	0.005	0.043	-0.042	0.053
	RMSE	0.023	0.039	0.026	0.052	0.048	0.051	0.033	0.014
	Observations	18	18	18	18	18	18	18	18

Table 11: Out-of-Sample Forecasting Metrics, 2020M07-21M12

Table 12: IP Growth next 12 months

coefficient	IN	СН	KO
constant	0.262	0.179	0.108
	0.032	0.057	0.038
spread	-3.322	3.099	1.252
	0.639	0.945	0.944
3 mo rate	-3.830	3.550	-2.371
	0.560	0.851	1.175
FCI		0.036	-0.108
		0.009	0.030
DSR		-1.248	
		0.161	
FTS	5.786	1.588	
	1.145	0.345	
Adj.R sq	0.366	0.728	0.243
N	85	189	219

Notes: OLS regression coefficients (Newey-West standard errors in parentheses). Bold face denotes significance at 5% marginal significance level.

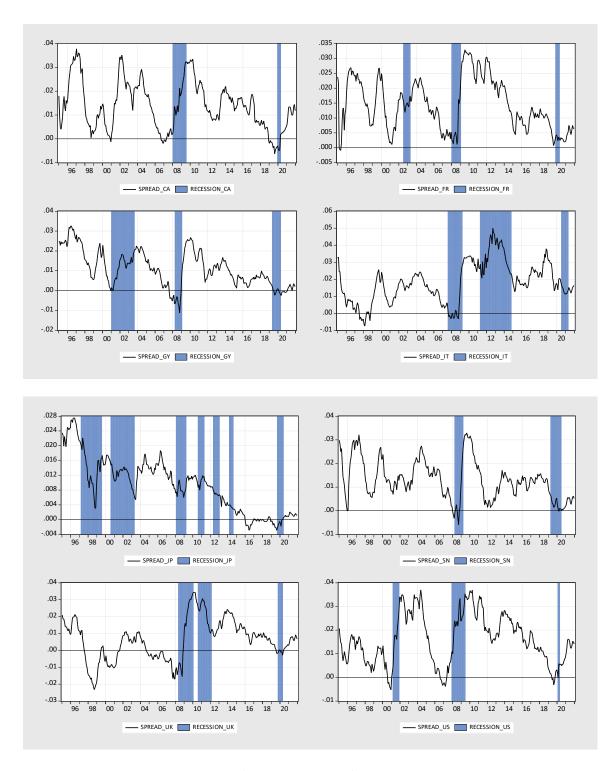
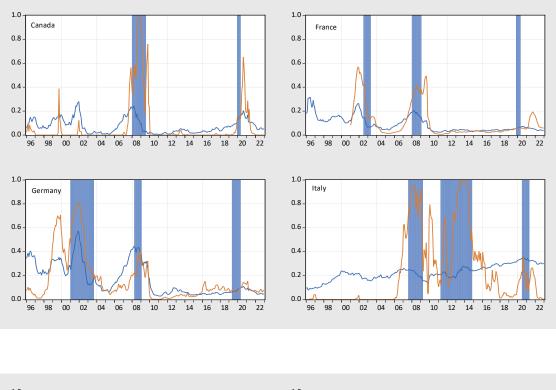


Figure 1: Recessions peak-to-trough (light blue shading) 10 year minus 3 month term spreads (black), for Canada, France, Germany, Italy, Japan, Sweden, UK, and US. Recession dates from ECRI, except NBER for US



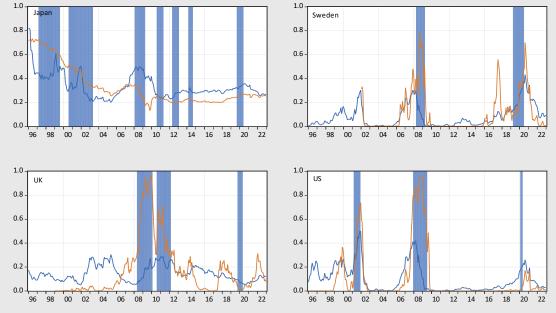


Figure 2: Recessions peak-to-trough (light blue shading) and estimated recession probabilities from term spread plus short rate (blue), and from full specification (red), for Canada, France, Germany, Italy, Japan, Sweden, UK, and US. Recession dates from ECRI, except NBER for US.

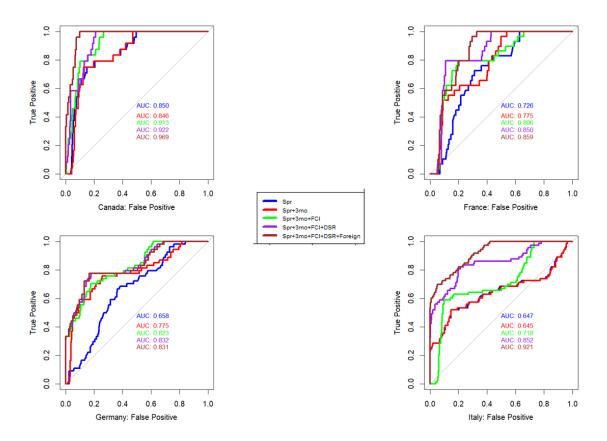


Figure 3a: AUC measures for Canada, France, Germany and Italy

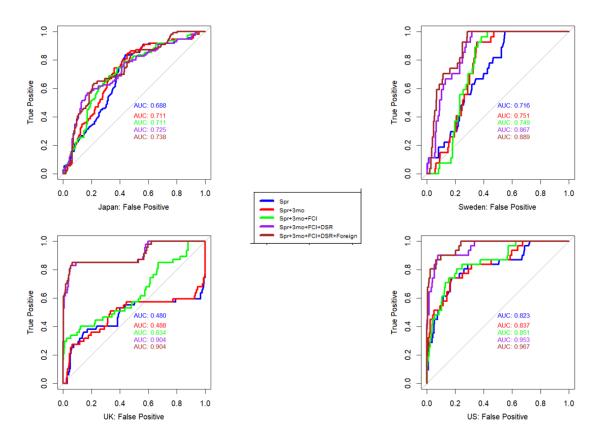


Figure 3b: AUC measures for Japan, Sweden, UK and US

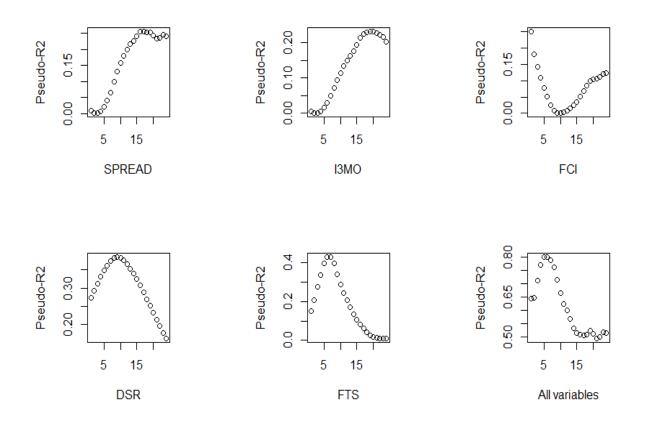


Figure 4: Optimal leads of each variable and the complete model with all variables for the US

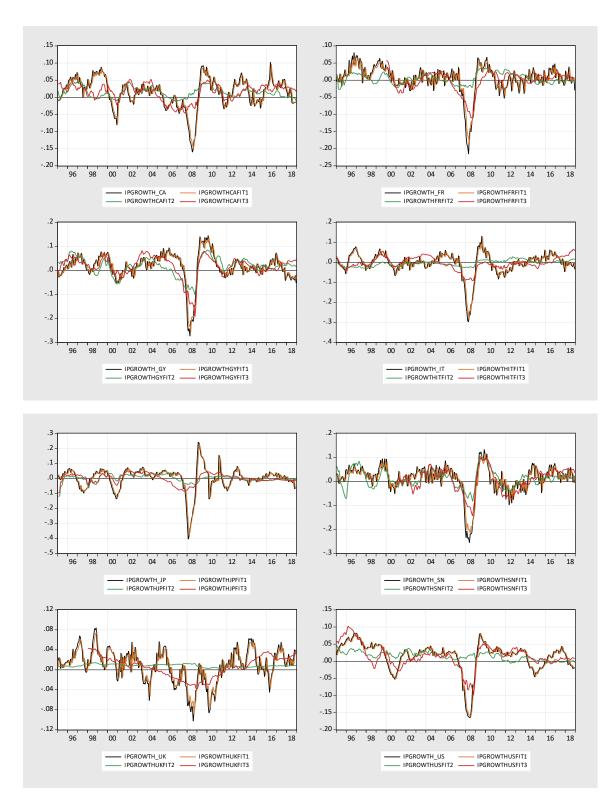


Figure 5: Industrial production growth rate for next 12 months, and fitted values for AR(1) (tan), spread plus short rate (green), and full specification (red), for Canada, France, Germany, Italy, Japan, Sweden, UK and US.

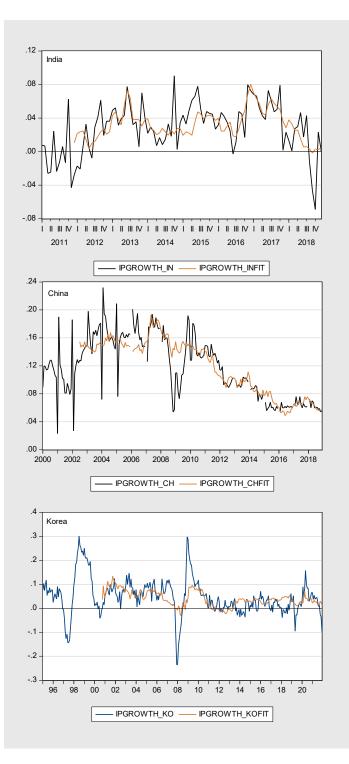


Figure 6: Industrial production growth for next 12 months (black), and in-sample regression fit (tan), for India (top panel), China (middle panel) and Korea (bottom panel)