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Forecasting the End of the Global Recession: Did We Miss the Early Signs?

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Abstract

This paper looks at the term-structure literature to identify early signs predicting recessionary patterns in the U.S. and other developed economies. Based on the National Bureau of Economic Research (NBER) and Economic Cycle Research Institute (ECRI) recession dates, we define the probability of recession as a function of the traditional yield spread, plus a forward-looking measure of growth expectations, namely the output gap growth spread. For other countries, we extend the model and make it additionally dependent on the probability of recession in the U.S. Our results indicate that most of the *a-posteriori* official recession dates could have been forecast as early as April 2009, when the first green shoots of recovery appeared in the U.S. data. Overall, the term-structure versions we apply allow us to signal recessions earlier and more accurately than traditional term-structure models and most professional forecasters.

JEL codes: F47, F37
Keywords: Forecasting, early recession signs, term structure, yield curve

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The summer of 2007 marked the beginning of the worst economic downturn in U.S. history since the Great Depression. Economic deterioration eventually spread. It took only a few months for the international economy to experience a similar downturn. This crisis marked the onset of a new financial and economic order, thrusting monetary and fiscal authorities into unfamiliar territory. The largely unforeseen episode impelled central banks and governments throughout the world to take unprecedented measures to prop up their economies at a time when they had a limited understanding of the full effects of their actions.

With many issues still to be addressed, virtually every developed country has officially emerged from recession.[1] The atypical nature of this recession serves as a unique learning experience. The challenge now is to draw some lessons that may be applied in future episodes. One interesting subject in this regard is the detection of early recessionary signs. The crisis emerged and ended largely unforeseen, even by professional forecasters. This research is motivated by empirical evidence suggesting that signs predicting the end of the U.S. recession may have appeared in the U.S. economy as early as the first quarter of 2009. With newly released data on recession dates, we look at the term-structure literature in an attempt to decipher early recessionary signs in the U.S. and other developed countries.[2]

With data as they existed in March–April 2009—which we believe marked the turning point in the recession—we define an extended term-structure model capable of *a-priori* predicting the end of the recession in the U.S. and other developed economies. The probability of recession is defined as a function of the traditional yield spread, plus a forward-looking measure of growth expectations, namely the output gap growth spread. Exploring one step further, we test recent evidence suggesting that movements in U.S. business cycles have a delayed effect on other countries' economic fluctuations, making their recession probabilities additionally dependent on the probabilities of recession in the U.S. We carry out the analysis for Canada, France, Germany, Italy, Japan, and the U.K. with data as they existed in March–April 2009.

Our results show that 1) the end of recession in the U.S. could have indeed been anticipated as early as April 2009 had the contemporaneous information been correctly (or in a timely manner) interpreted, and 2) that other countries' recessionary patterns, which are shown to be dependent on the probability of recession in the U.S., could have been foreseen then as well. Our extended term-structure models proved to be effective in the detection of turning points, which could eventually enable policymakers and governments everywhere to act proactively in the face of adverse economic conditions.

Section 1 presents anecdotal evidence suggesting that the turning point of the economic downturn became evident in March–April 2009 but was underestimated by most professional forecasters. The next section details the extended term-structure model for the U.S., which, apart from using the customary yield spread, introduces a forward-looking measure representing the output gap growth spread. This section also presents the in-sample and out-of-sample results for the probability of recession in the U.S. Section 3 tests how well this extended term structure works for other countries and compares performance when the functional form additionally depends on current and lagged U.S. recession probabilities. Section 4 poses policy relevance questions.

1. MOTIVATION: DID WE MISREAD THE SIGNALS IN SPRING 2009?

After a few quarters of an unprecedented global economic contraction, surprising signs started to emerge in the U.S. in March 2009 that suggested the rate of output decline had moderated. Unlike they did in the rest of the world, financial conditions somewhat improved in the U.S. and confidence indicators (for the first time in months) reported levels slightly greater than anticipated. Despite the moderate improvement in some important indicators, few forecasters felt confident declaring that the end of the recession was in sight.

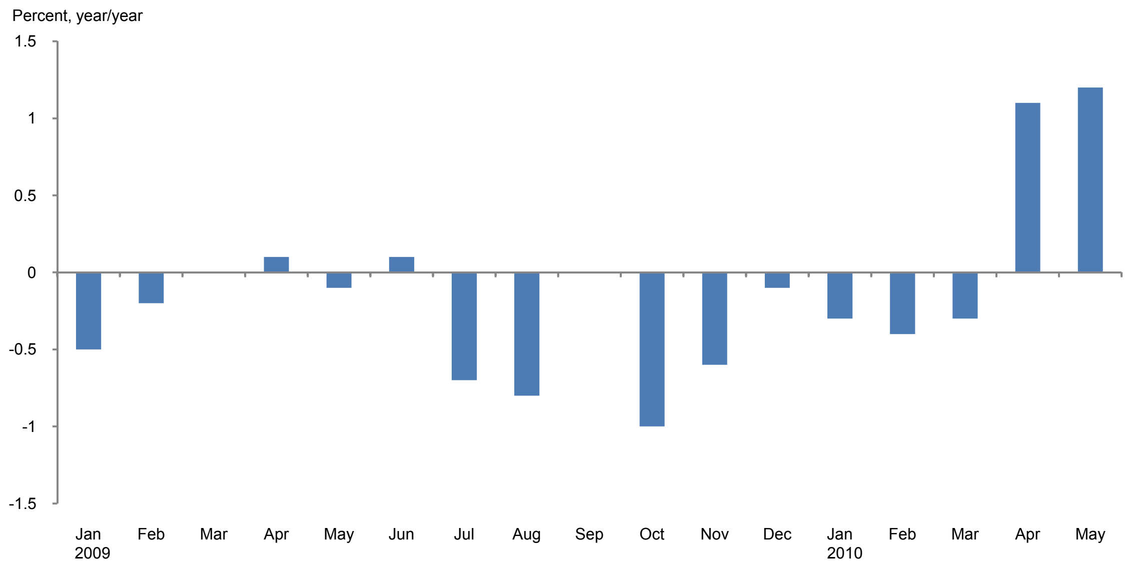
The Goldman Sachs Financial Stress Index (FSI) in March was the first indicator suggesting a sizable improvement in market conditions in the U.S., with economic data indicating a stabilization of the cycle. Shortly thereafter, the Organization for Economic Cooperation and Development (OECD) and American Bankers Association's Economic Advisory Committee (EAC) both issued forecasts considered optimistic at the time. The OECD expected the U.S. resurgence to begin with flat growth in third quarter 2009. The EAC projected that the U.S. economy would emerge from recession by late summer 2009, with economic activity increasing 0.5 percent between July and September. We now know that the EAC's upbeat forecast fell short of actual growth (2.3 percent).

April's data proved slightly more compelling, convincing a few more forecasters that the turning point may have been reached. That month, the U.S. Blue Chip's leading indicator jumped into positive territory (*Figure 1*) at the same time *Consensus Forecasts* stabilized and the pace of negative growth receded (*Figure*

[1] The official recession dates used in this paper are based on NBER for the U.S. and ECRI for other countries.

[2] ECRI's business cycle peak and trough dates, updated in March 2011.

Figure 1: Blue Chip Leading Economic Indicator Turns Positive in April 2009



2). Figure 2 shows the U.S. gross domestic product (GDP) quarterly forecasts for first quarter 2009 though fourth quarter 2010, as published in the November 2008 and February, March, April, and May 2009 issues. Second quarter 2009 represents the point at which expectations turn. We also see that growth expectations stabilize in March–May 2009. The readings of November 2008 and February 2009 illustrate the prevailing volatility prior to that. Nevertheless, the relatively good news in March–April had only a moderate impact on the growth projections of professional forecasters. Most of them seemed to concur that the U.S. would emerge from recession slightly sooner than previously thought—albeit not as soon as it did.

Figure 2: Quarterly Consensus Forecasts Stabilize in March–May 2009

In retrospect, we see that the signs must have been there, but the pessimism in the economic status quo brought about by a recessionary environment may have caused forecasters to undershoot, even in the face of the March–April news. It is now clear that we were closer to the end of the U.S. recessionary cycle than most of them had anticipated.

Furthermore, if the U.S. exerts a lagged influence over other countries' economic fluctuations, as recent literature suggests, these early recovery signs in the U.S. might have allowed policymakers in other countries to act proactively. The motivation behind this research was the possibility that the incipient green shoots in March–April contained information that was not correctly or timely interpreted but nonetheless impacted the real economy.

2. FORECASTING RECESSION PROBABILITIES FOR THE U.S.

Defining a Term-Structure Model for the U.S.

The yield curve describes the relationship between short- and long-term interest rates (i.e., the term spread). The shape and slope of the curve are closely scrutinized because empirical studies have proven their connection to expectations of future interest rates and economic activity (Dueker 1997; Estrella and Hardouvelis 1991; Estrella and Mishkin 1997, 1998; Estrella and Trubin 2006; Kozicki 1997). In general, the flattening of the curve is indicative of lower future spot-rate expectations, which are usually related to an expected worsening of future economic conditions. The steeper the slope, the slower the expected growth in real output, and vice versa. Consequently, an inverted yield curve—in which shorter-term yields are higher than longer-term yields—is largely associated with future recessions. Anecdotal evidence seems to corroborate this relationship. In nine out of the last ten U.S. recessions, an inverted yield curve has preceded a downturn.

There are several theoretical approaches explaining the relationship between the yield curve and future economic activity. The consumption capital asset pricing model (CCAPM) (Campbell and Cochrane 1999), the Real Business Cycle Theory (RBC) (Kydland and Prescott 1988), and the Keynesian IS-LM models (Estrella and Hardouvelis 1991) all seem to be consistent with the observed predictability of the yield curve.[3] However, these and other explanations have proven flawed. As of today, no standard theoretical approach exists to relate the yield curve to forecasts of future economic activity, and it is not clear whether the yield curve signals expectations of monetary policy alone, information about future economic conditions, or both (Kozicki 1997).[4] The transmission channels have not been clearly identified, and the curve's close association with subsequent changes in production, consumption, investment, and other components of real GDP remains purely empirical.[5]

While the theoretical underpinnings of the yield curve as a leading indicator are a matter of debate, the empirical evidence is hard to refute. The curve is a de facto leading indicator, and its predictive power for in-sample and out-of-sample performance has empirically surpassed most of the variables typically used as predictors of the U.S. economy (Estrella and Mishkin 1998), including leading indicators and survey forecasts (Estrella and Hardouvelis 1991; Dueker 1997).[6] Its predictive value is well-recognized by public and private forecasters in the U.S.[7]

The empirical relationship between future production rates and the current slope of the yield curve seems to be stronger when the economy is close to or in recessionary mode (Estrella and Hardouvelis 1991). This asymmetry has suggested that the yield curve may be a better predictor of a binary variable that indicates either the presence or absence of recession. While some evidence indicates that the binary models may overpredict recession results (Chauvet and Potter 2005), research has also shown them to be more effective and stable than continuous models (Estrella, Rodrigues, and Schich 2003). Hence, a great deal of related research has been conducted with probabilistic models such as logit or probit (Stock and Watson

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[3] The CCAPM describes the relationship between real interest rates and real consumption growth, independent of changes in monetary policy. The RBC literature relates expected productivity shocks to the slope of the yield curve. The intuition behind the correlations generated by a business-cycle model is the same as in the CCAPM. Keynesian specifications combine real output with the expectations hypothesis in such a way that when output falls, short-term rates drop relative to longer maturities. The results of Keynesian models are analogous to those of the CCAPM and RBC models.

[4] In fact, existing evidence neither confirms nor rules out the possibility that some of the predictive power of the yield curve comes from the stance of monetary policy. In the risk- or term-premium literature, it is argued that the curve reflects the stance of monetary policy; here, if current rates are low, current monetary policy is tight and is therefore expected to loosen in the future (i.e., longer-term rates are expected to be lower). However, believers of the credit market theory think that the yield spread contains information on credit market conditions. Here, a rise in long-term yields is caused by an increase in current demand for credit, which in turn is promoted by current low rates. There is no clear winner in the literature.

[5] Most recently, a growing interest in the causality of macroeconomic variables and the future path of the yield curve has revealed the possibility of a bidirectional relationship (Bernadell, Coche, and Nyholm 2005). Diebold, Rudebusch, and Aruoba (2006), for instance, find evidence of both macroeconomic effects on the future yield curve and yield curve effects on future macroeconomic developments. For this paper, however, we assume a causality going from the yield curve to future economic growth.

[6] For instance, in in-sample estimations, the U.S. Department of Commerce composite index of leading indicators, a widely cited and influential economic series, has been shown to provide little or no advance warning of business-cycle turning points. Its predictive horizon has also proven to be short compared with that of the yield curve (Koenig and Emery 1991).

[7] For instance, the Conference Board uses the yield spread in the construction of its Leading Economic Index.

1989; Estrella and Mishkin 1998).[8] However, this type of literature is mainly focused on predicting recessions rather than considering quantitative measures of future economic activity.

Because the focus of this section is to forecast recessions in the U.S., we use this trend of research to define our base model. Specifically, we apply a probit model, which has proven to be very successful and stable with U.S. data. We extend the probability of recession—traditionally defined as a function of the yield spread exclusively—to make it dependent on a forward-looking measure of growth expectations, namely the output gap growth-rate spread.

The inclusion of the output gap growth-rate-spread term is an important addition to the traditional term-structure models and, more generally, to the overall analysis of the yield curve as a leading indicator. Several hypotheses argue that the yield spread's predictive power for real growth derives from the forward-looking information it contains, and most of the intuition behind such power relies upon the expectations hypothesis.

The general argument is that agents incorporate current expectations about the future state of the economy into current asset prices. However, a great deal of vagueness is associated with the composition and fabrication of these expectations.[9] There is evidence that the predictive power of the yield spread comes from multiple channels —which are often hard to identify—and not exclusively from expectations about the future state of the economy (Estrella and Trubin 2006). By including the output gap growth-rate spread, we separate the effects of expectations of future output growth from other unidentified influences.[10]

Finally, we allow different lag specifications in order to obtain some information on the delay with which the yield spread or the output gap spread affects the probability of recession in the U.S. Our general extended probit representation is defined as:

$$Pr(U.S.Recession)_{t+h} = F(C, dr_t, dr_{t-1}, dr_{t-6}, dr_{t-12}, dg_t, dg_{t-1}, dg_{t-6}, dg_{t-12}), \tag{1}$$

where $Pr(U.S.Recession)_{t+h}$—the probability of recession h months ahead of the current month t—is a (dummy) variable equal to 1 when the month is identified as recessionary by the NBER,[11] and zero otherwise, C is a constant term, dr is the yield spread, and dg is the output gap growth-rate spread.[12]

The yield spread (dr) is defined as the monthly difference between the U.S. government bond yield ten years and over (our proxy for long-term interest rates) and three-month certificates of deposit (our proxy for short-term rates) as posted in the OECD main economic indicators online database.[13] The output gap growth-rate spread (dg) represents the monthly difference between the one-year-ahead and current annualized real growth rates.[14] To calculate this, we pull the nonannualized quarter-over-quarter real GDP growth rate from the OECD Main Economic Indicators' National Accounts for second quarter 1984 to fourth quarter 2008 (the last quarter available in March 2009) and the annualized *Consensus Forecasts* quarter-over-quarter expected real GDP growth rate for first- through fourth-quarter 2009.[15] To merge the two

[8] Both logit and probit are probability models wherein the dependent variable is a probability between 0 and 1 (the probability of recession in this case). They both have symmetric distributions. In the probit model, a standard normal transformation is used to constrain the probability of falling between 0 and 1, while in the logistic distribution, the error term follows an extreme value distribution that gives it fatter tails than the normal distribution.

[9] Apart from expectations regarding future output growth, agents may make assumptions about the future direction of monetary policy or react to their own perception of the current economic environment. Under volatile conditions, these expectations usually obey other undetermined and highly unpredictable factors.

[10] A well-defined characterization of expectations of future real growth is increasingly important in the term-structure literature. Ang, Piazzesi, and Wei (2006), for instance, build a dynamic model for GDP growth and yields that completely characterizes expectations of GDP. Orphanides and van Norden (2005) show evidence regarding the value of the output gap growth rate as a reliable predictor of the real economy, especially in forecasting exercises. And other authors, including Nikolsko-Rzhevskyy (forthcoming), have found that replacing inflation or output gaps with their forecasts provides better descriptions of historical policy.

[11] The official NBER recession dates can be found at www.nber.org/cycles.html.

[12] We recognize that some overlap may occur with the coefficient of the yield spread (specifically its twelfth lagged value), picking up some of the effects of the output gap growth spread, which represents year-ahead expectations. However, such overlap should be very low in times of abnormally high risk aversion or panic, generally present in recessionary situations.

[13] Data can be obtained from the OECD website (www.oecd.org).

[14] A similar definition is used in Orphanides and van Norden (2005). In this article, the authors find that forecast-based variables better describe the evolution of monetary policy in the U.S. (i.e., the Taylor rule). Particularly relevant for our work is their forward-looking output gap characterization, defined as a year-ahead growth forecast relative to potential.

[15] The one-year-ahead and current annualized real growth rates can be pulled from the OECD website (www.oecd.org). The quarterly output gap data can be obtained from the March 9, 2009, *Consensus Forecast* survey.

datasets, we annualize the OECD data and form a single compatible quarterly data series, from which we define a *quarterly* output gap growth rate as:

$$dg_n = \left(GDP_{gr}\right)_{n-4} - \left(GDP_{gr}\right)_n ,$$

where $(GDP_{gr})_n$ is the annualized quarterly real growth rate.[16] We then do a monthly frequency conversion of dg_n following Levin and Taylor (forthcoming) that defines the monthly output gap growth rate, dg_t, used in (1).[17]

Table 1: In-Sample Results, U.S. (h=0)

	Models						
	1	**2**	**3**	**4**	**5**	**6**	**7**
C	-2.89	-2.91	-3.10	-3.10	-1.99	-1.81	-1.83
	(0)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
dr	-0.61	-.028	-0.10				
	(0.57)	*(0.77)*	*(0.92)*				
dr(-1)	2.50	20.15	1.65	1.56	0.98		
	(0.06)	*(0.09)*	*(0.14)*	*(0.02)*	*(0.01)*		
dr(-6)	-2.81	-2.98	-2.96	-2.94	-1.84	-0.84	-0.88
	(0.01)	*(0.01*	*(0.01)*	*(0.01)*	*(0)*	*(0.01)*	*(0.01)*
dr(-12)	-1.12	-1.07	-1.05	-1.04		-1.20	-1.08
	(0.03)	*(0.04)*	*(0.03)*	*(0.03)*		*(0)*	*(0.01)*
dg	2.30	2.17	2.20	2.20	1.50	1.17	0.74
	(0)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
dg(-1)	-1.45	-1.37	-1.42	-1.42	-0.90	-0.45	
	(0.02)	*(0.01)*	*(0.02)*	*(0.02)*	*(0.01)*	*(0.15)*	
dg(-6)	-0.38	-0.39					
	(0.34)	*(0.32)*					
dg(-12)	-0.43						
	(0.36)						
MFR	0.82	0.82	0.81	0.81	0.71	0.75	0.74
HQ	0.27	0.26	0.25	0.24	0.32	0.26	0.26
AIC	0.22	0.21	0.21	0.20	0.29	0.23	0.24
BIC	0.6	0.34	0.32	0.29	0.36	0.31	0.30

NOTE: P values in parentheses.

In-Sample Results

We use (1) to determine the probability that the U.S. is in recession, based on data from January 1991 to March 2009 as it existed in April 2009. Various specifications were considered, with the objective of comparing performance. Table 1 presents the in-sample results for the most significant model definitions considered: All the models seem to be fairly good representations of the probability of recession in the U.S., with the McFadden R-squared (MFR) terms fitting between 71 and 82 percent of the data.[18]

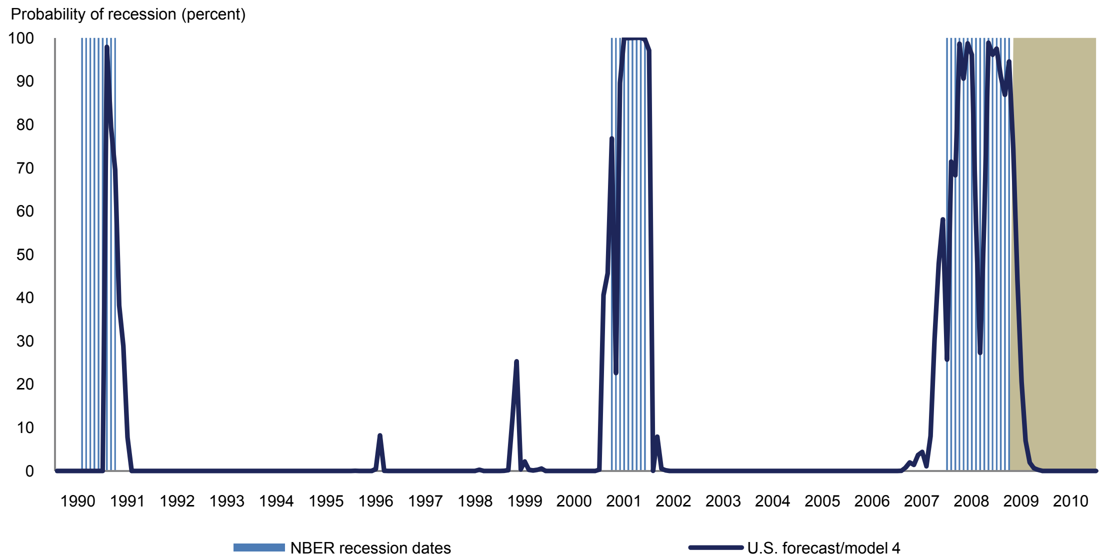
However, high p values in current dr in models 1, 2, and 3 indicate that this variable may not belong in the equation. The same is true for the sixth and twelfth lags of dg in models 1 and 2. This may suggest that the yield spread takes longer than the growth rate in the output gap to show in the probability of recession.

[16] We index quarterly dates with n to differentiate them from monthly dates, for which we use t throughout the paper.

[17] These authors construct pseudo-real-time data by taking a linear average of semiannual data on one-year-ahead inflation expectations from the Livingston Survey to convert it into quarterly data. The main difference in our approach is that we use a quadratic smoothing algorithm instead of linear methodology.

[18] The McFadden R-squared is analog to the R-squared reported in linear regressions and provides a measure of in-sample accuracy. It represents the likelihood ratio index of the restricted and unrestricted regressions, always lying between 0 and 1.

Figure 3: U.S. Model 4's In-Sample and Out-of-Sample Forecasts Largely Coincide With NBER Recession Dates



NOTE: The shaded area (right) denotes the out-of-sample forecast.

The signs of the coefficients seem consistent. In all the models, the yield spread's coefficient is positive in the first lag and negative in the sixth and twelfth lags. A normal yield curve (positive dr) in the current period would be associated with a future increase in real economic activity, which would intrinsically add to the probability of contemporary recession. Six or twelve months ahead, these expectations would have had time to materialize, inversing their effects on the probability of recession. It is important to notice that this reversion more than overturns the original impact on the probability of recession.

Similarly, for the output gap growth-rate spread (dg), a positive value would indicate that one-year-ahead growth is expected to be stronger than the present-day rate, adding to the current probability of recession. For this variable, we see that the effects on the probability of recession partially dissipate in one month as some of these expectations materialize, and they become irrelevant six and twelve months later. It is important to notice that the immediate effect of dg is rather large in all the models, but it decreases by at least half in the following month. This suggests that, as in the case of the yield spread, economic agents tend to overestimate the direction of the future economy, only to correct once new information is available.

To formally choose the best specification, we primarily looked at the highest MFR values and the lowest values for the Hannan–Quinn (HQ) criterion, which are both especially suited for binary model settings. For completeness, we also looked at the lowest values of the Akaike and Bayesian information criteria (AIC and BIC, respectively).[19] From the seven models analyzed, the highest MFR values corresponded to model 1, closely followed by models 2, 3, and 4 (all above 81 percent). However, we chose model 4 as the best representation because it had significantly lower values for the HQ, AIC, and BIC criteria and because all its variables were significant, which was not the case in the other models with high-fitting values. We compared the predictions (or fitted values) obtained from model 4 with the official NBER recession dates. We obtained an almost perfect in-sample fit (*Figure 3*), identifying the last three recessions with remarkable precision.

Out-of-Sample Forecasts

Model 4, our best representation of actual NBER recessions, was used to forecast out-of-sample the probabilities of recession in the U.S., with predictive horizons ranging from one to nine months ($h = 1...9$). The coefficients estimated for each horizon, along with the respective p values, are presented in Table 2. The actual probabilities of recession, obtained by plugging in the corresponding coefficients for horizons $h = 1...9$ into the last data point available, are presented in Figure 4. The forecasts, calculated with data as they existed in April 2009, show a steep reduction in the probability of recession from June to July, with the probabilities virtually dissipating by August–September. This coincides with the NBER's subsequent

[19] The AIC and BIC information criteria for model selection look at the difference between the log likelihood values of the restricted and unrestricted versions of the equation, with the BIC criterion imposing a larger penalty for additional coefficients. HQ is a similar model-selection criterion used in binary-model settings.

announcements. These results suggest that our extended term structure could be a good predictor of the U.S. real economy because it anticipated the end of the U.S. recession as early as the beginning of second quarter 2009. Our model's success may owe to the fact that both the yield spread and the output gap growth spread contain forward-looking information. Theory suggests that recession indicators produced by the yield curve in its original form may significantly precede those produced by other indicators. Adding another explicitly forward-looking variable might have signaled recessions earlier (and presumably more accurately) than traditional yield curve models used by most professional forecasters.

Figure 4: U.S. Model 4's Out-of Sample Probabilities of Recession for One Through Nine Months Ahead

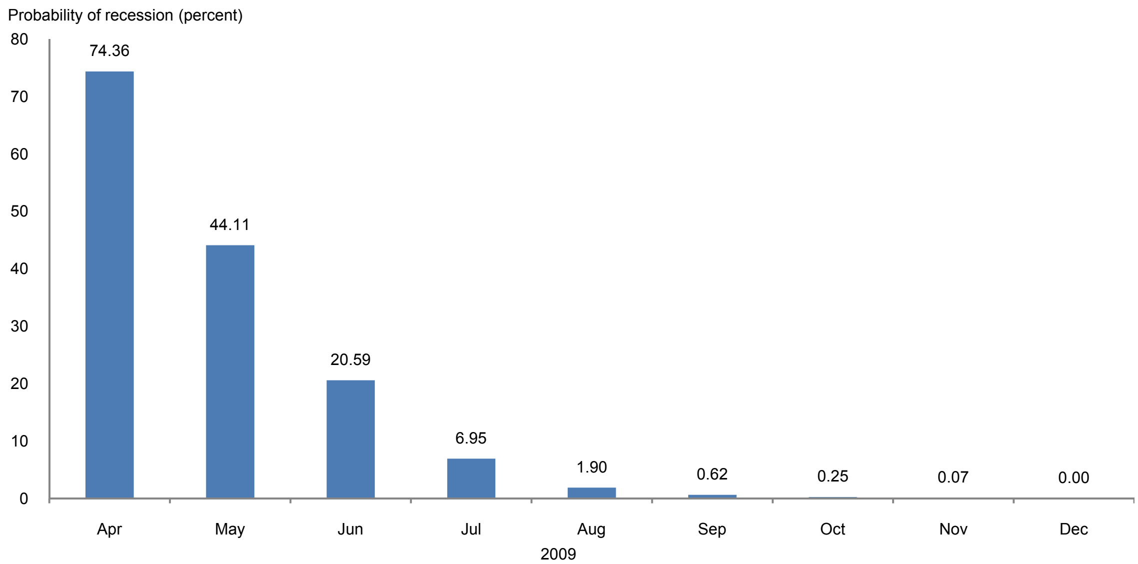


Table 2: Out-of-Sample Forecasts, U.S. (April–December 2009)

	Forecasting horizon, h								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
C	-2.57	-1.40	-1.15	-0.85	-0.65	-0.50	-0.41	-0.36	-0.26
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.03)*	*(0.07)*	*(0.11)*	*(0.25)*
dr(-1)	1.31	0.41	0.31	0.01	-0.22	-0.52	-0.75	-0.88	-1.07
	(0.01)	*(0.17)*	*(0.27)*	*(0.96)*	*(0.39)*	*(0.05)*	*(0.00)*	*(0.00)*	*(0.00)*
dr(-6)	-2.81	-1.39	-1.27	-1.05	-0.97	-0.79	-0.66	-0.53	-0.31
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.02)*	*(0.06)*	*(0.14)*	*(0.43)*
dr(-12)	-0.84	-0.62	-0.55	-0.67	-0.69	-0.76	-0.78	-0.77	-0.91
	(0.05)	*(0.10)*	*(0.12)*	*(0.06)*	*(0.05)*	*(0.04)*	*(0.03)*	*(0.04)*	*(0.01)*
dg(-1)	2.06	0.88	0.76	0.63	0.41	0.11	-0.22	0.23	0.50
	(0.00)	*(0.00)*	*(0.00)*	*(0.01)*	*(0.10)*	*(0.69)*	*(0.95)*	*(0.46)*	*(0.14)*
dg(-6)	-1.44	-0.50	-0.50	-0.42	-0.23	0.08	0.22	-0.08	-0.47
	(0.00)	*(0.07)*	*(0.07)*	*(0.13)*	*(0.42)*	*(0.79)*	*(0.51)*	*(0.81)*	*(0.22)*
MFR	0.76	0.63	0.56	0.52	0.50	0.49	0.50	0.51	0.52
HQ	0.27	0.37	0.41	0.44	0.46	0.46	0.46	0.46	0.45
AIC	0.24	0.33	0.37	0.40	0.42	0.42	0.42	0.42	0.41
BIC	0.33	0.42	0.46	0.49	0.51	0.52	0.51	0.51	0.51

NOTE: P values in parentheses.

3. FORECASTING RECESSION PROBABILITIES FOR OTHER COUNTRIES

In the previous section, we looked into the term structure as a predictor of real economic activity and defined a model capable of *a-priori* predictions of U.S. recession probabilities. We now extend the analysis to other developed economies, an appealing approach given the limited evidence on the usefulness of the yield spread as a predictor of real economic activity outside the U.S.[20]

Capitalizing on the U.S. forecasts obtained in the previous section, we use our extended term-structure framework to test recent evidence suggesting that movements in U.S. business cycles have a delayed effect on other countries' economic fluctuations (Fernandez and Nikolsko-Rzhevskyy 2010).[21] If this were true, the probability of recession in other countries would depend not only on those nations' own yield and output gap-growth spreads but possibly on the probabilities of recession in the U.S. This possibility is worth exploring because it seems consistent with what occurred in the last recession. First, we know that the earliest signs foretelling the crisis emerged in the U.S. and extended throughout the world. Second, the results of our U.S. forecasting exercise suggest that real signs of recovery surfaced in this country earlier than anywhere else.[22]

Accordingly, our exercise begins with the selection of the best characterization of the probability of recession for country i, F_i^*, where F_i^* depends exclusively on the yield spread and output growth rate (and lags). We then define $F_i^{*U.S.}$ as the best characterization when the functional form additionally depends on current and lagged U.S. recession probabilities (as obtained in the previous section). We carry out the analysis for Canada, France, Germany, Italy, Japan, and the U.K., for which we compare performance among F_i^* and $F_i^{*U.S.}$.[23] Due to availability, the data used in this section range from August 1992 to March 2009. The probit definitions for the probability of recession in country i at time t, with and without the U.S. probability of recession, are:

$$Pr(Rec)_{t+h}^{i} = F_i^*(C, dr_t^i, dr_{t-1}^i, dr_{t-6}^i, dr_{t-12}^i, dg_t^i, dg_{t-1}^i, dg_{t-6}^i, dg_{t-12}^i), \tag{2}$$

$$\begin{aligned} Pr(Rec)_{t+h}^{i} \quad = \quad & F_i^{*U.S.}(C, dr_t^i, dr_{t-1}^i, dr_{t-6}^i, dr_{t-12}^i, \\ & dg_t^i, dg_{t-1}^i, dg_{t-6}^i, dg_{t-12}^i, usf4_t^i, usf4_{t-1}^i, usf4_{t-6}^i, usf4_{t-12}^i)\ , \end{aligned} \tag{3}$$

where $Pr(Rec)_{t+h}^{i}$ is the probability of recession in country i, h periods ahead of month t. It is represented by a dummy variable that takes the value of 1 if the country is said to be in recession according to ECRI, and zero otherwise.[24] The yield spread and output gap growth spread for country i at month t are represented by dr_t^i and dg^i, respectively, which, for consistency, are estimated with the same methods and sources used for the U.S. In (3), $usf4_t^i$ and lags denote the U.S. probability of recession, as obtained in the previous section for model 4, our preferred specification. For consistency, we test the first, sixth, and twelfth lagged values for all the variables.

F_i^* and $F_i^{*U.S.}$ are selected from a number of lag combinations based on the highest MFR values and the lowest HQ, AIC, and BIC information criteria. As we did with the U.S., when two or more alternative

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[20] See Bonser-Neal and Morley (1997).

[21] In a strict real-time analysis, and using a long dataset (1960 to 2007), these authors decompose the quarterly GDP series of eleven countries into trends and cycles using the Watson (2007) version of the Baxter and King (1999) band-pass filter. Then they apply both rolling and expanding windows of different sizes to analyze the historical evolution and causal relationship of the business-cycle movements of the U.S. and other countries, concluding that since the mid-1980s, U.S. economic fluctuations have affected other countries with a delay rather than contemporaneously. They also find that the U.S. influence now shows up gradually, taking longer for the full effect of a shock to the U.S. business cycle to manifest in other economies.

[22] If our extended term-structure model were able to predict the end of the U.S. recession with the exclusive use of data available as of April 2009, recovery signs must have indeed emerged in the country at a time when the world's economic outlook was extremely pessimistic.

[23] Our initial intention was to include the European Union and the rest of the G-7 countries, but no statistics are published for this block in the ECRI, the source we use to date recessions.

[24] We use ECRI data for consistency because the institute calculates business-cycle peaks and troughs with the same methodology used by the NBER in establishing official business-cycle dates for the U.S. For both NBER and ECRI, a recession is defined as a significant decline in economic activity across the economy that lasts more than a few months and is normally visible in real GDP, real income, employment, industrial production, and wholesale−retail sales. The ECRI publication with the recession start and end dates can be found at www.businesscycle.com/resources/cycles.

specifications had fairly close fitness and information criteria values, we gave preference to those functional forms in which the explanatory variables had the best significance levels (i.e., the lowest p values). Our selected functional forms and the corresponding in-sample results are presented in Table 3. The results for F_i^* show a relatively good fit, with MFR values going from 23 percent for Germany to above 70 percent for Italy, the U.K., and Canada. The information criteria values are stronger for Canada and the U.K. (which lie within the range of values obtained for the U.S.) and weaker in Germany and Japan. We also see that all the variables are highly significant, with zero p values virtually everywhere. Looking at the signs of the coefficients, we see that positive values for current yield spread and output gap growth spread are generally associated with expectations of more favorable economic conditions in the future, implicitly adding to the probability of recession at present. Overall, negative coefficients are seen in later periods, when more information becomes available and the impact of the original expectations is corrected. Based on the results for F_i^*, we may conclude that agents tend to overestimate the future state of the economy, only to correct once additional information becomes available. The opposite seems to be true for Japan, which may be attributable to the country's comparatively low interest rate structure.

The results for $F_i^{*U.S.}$ show that the influence of the U.S. is significant in the probability of recession in other countries. Without exception, the inclusion of U.S. probabilities of recession substantially increases the goodness of fit and decreases the information criteria. The $F_i^{*U.S.}$ MFR values' increase with respect to F_i^* is especially noticeable for Germany (0.448 from 0.226) and Japan (0.555 from 0.339). But they are also important for Italy (0.796 from 0.715), the U.K. (0.865 from 0.712), and Canada (0.800 from 0.725). While information criteria decrease for all, the decline is especially noticeable for Germany and Japan.

The signs of the coefficients and the significance levels are consistent with those obtained from the F_i^* calculations. On one hand, we see positive values for current yield spread and output gap growth rates and negative values for their lagged coefficients. On the other hand, we see zero p values virtually everywhere, suggesting that the regressors belong in the equation. Japan, a country with a very different interest and inflation structure, responds in the opposite direction regarding the yield spread. For this country, an increase in interest rates generally overshoots a decrease in the current probability of recession, only to correct in later periods.

Without exception, all the countries depend on lagged values of U.S. recession probabilities, which adds to the evidence presented in Fernandez and Nikolsko-Rzhevskyy (2010). This is significant because recognizing recessionary signs early on in the U.S. could enable economic agents and monetary authorities across the world to respond preemptively, possibly attenuating the effects of an eventual economic downturn.

The predictions (or fitted values, $h = 0$) obtained from $F_i^{*U.S.}$ are compared with the latest official business-cycle peak and trough dates of the ECRI. We use the institute's dates available as of September 23, 2010, in assessing our forecasts. We then forecast the out-of-sample probabilities of recession for horizons $h = 1 \dots 15$. Data availability and the specific functional-form definitions determine each country's forecasting dates. Accordingly, the out-of-sample forecasts go from March 2009 to May 2010 for Italy and Japan, from April 2009 to June 2010 for France and Germany, and from April 2009 to December 2010 for the U.K. and Canada. The functional-form definitions for these last two countries allow us to use the six-steps-ahead probabilities of recession for the U.S. obtained in the previous section, which extends the forecast by six months. For these countries, we fit the model for $h = 0$ and immediately obtain the forecasts of recession probabilities six periods ahead without doing direct forecasts. The direct forecast begins in October 2009 ($h = 1$) and ends in December 2010 ($h = 15$).

Figures 5 to 10 plot the in-sample and out-of-sample recession forecasts ($h = 0 \dots 15$) against the most up-to-date business-cycle peak and trough dates as published by the ECRI in March 2011. The shaded area at the end shows the beginning of the out-of-sample exercise. The in-sample fit is rather accurate, identifying entry and exit recession points with significant precision. The path of the out-of-sample forecasts largely coincides with that of the ECRI dates.

Looking at countries independently, we see that for Italy, our in-sample forecast portrays remarkably well the beginning of the last recession, and the out-of-sample forecast depicts accurately the sharp decrease in recession probabilities and the eventual end of recession. In the case of France, our forecast pattern clearly increases with the presence of recessions. That is true for the last two recessions, but while our in-sample forecast begins in August 1993 after the 1992–93 recession in France, we see that the probabilities move toward zero with the end of the ECRI-dated recession. The out-of-sample forecast's turning point clearly coincides with the end of the downturn. In the last months of the forecast, we see that the recession probabilities wiggle a little, but the overall tendency is downward.

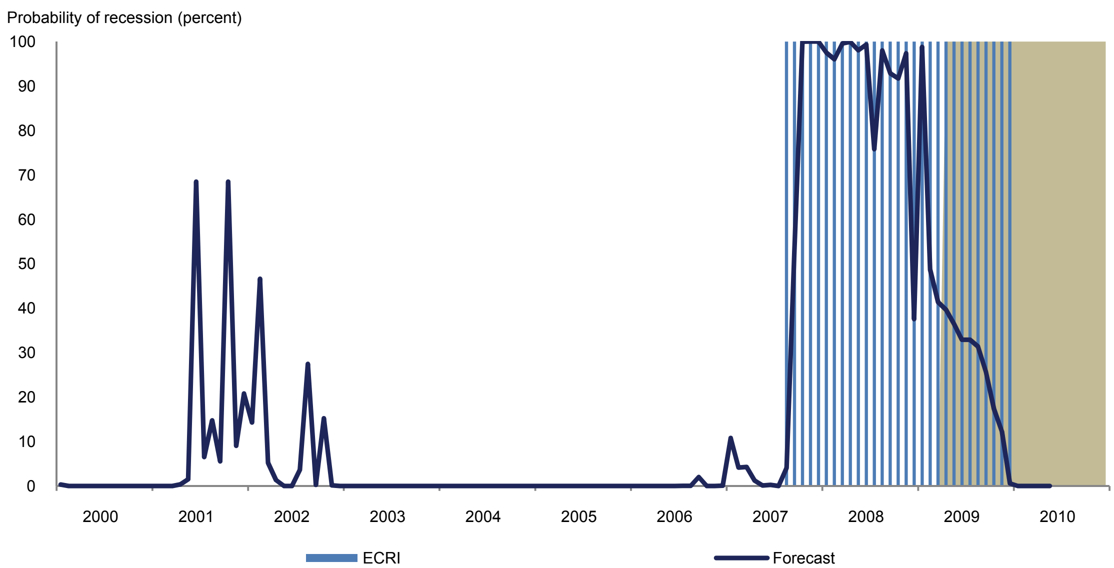
(Continued on page 15)

Table 3: In-Sample Results (h=0) for Other Countries' Most Significant Specifications

	Italy		**France**		**Japan**		**Germany**		**U.K.**		**Canada**	
C	2.70	6.51	-0.83	-1.38	1.26	-0.79	0.98	-1.36	-3.69	-16.19	-3.07	-1.79
	(0.03)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.19)*	*(0.00)*	*(0.02)*	*(0.00)*	*(0.08)*	*(0.00)*	*(0.00)*
dr					-2.23	-2.10		1.41			0.89	
					(0.00)	*(0.00)*		*(0.07)*			*(0.05)*	
dr(-1)	-0.86	-1.24						-1.84				
	(0.05)	*(0.04)*						*(0.03)*				
dr(-6)			-0.45	-0.27			-0.73	-0.85	0.86	3.18		-2.99
			(0.00)	*(0.04)*			*(0.00)*	*(0.07)*	*(0.00)*	*(0.13)*		*(0.02)*
dr(-12)	-3.38	-6.21			1.21	2.03	-0.39	1.27	-1.69	-2.80	-2.87	-1.92
	(0.00)	*(0.00)*			*(0.00)*	*(0.00)*	*(0.08)*	*(0.01)*	*(0.00)*	*(0.23)*	*(0.00)*	*(0.06)*
dg			0.23	0.13	0.13	0.15	0.10					
			(0.00)	*(0.04)*	*(0.00)*	*(0.00)*	*(0.01)*					
dg(-6)	-0.28	-0.21	-0.21	-0.11	-0.05						-0.53	
	(0.02)	*(0.09)*	*(0.00)*	*(0.10)*	*(0.04)*						*(0.00)*	
dg(-12)	-0.19	-0.37						0.10	-0.96	-2.49	-0.56	-0.38
	(0.07)	*(0.01)*						*(0.11)*	*(0.00)*	*(0.10)*	*(0.00)*	*(0.00)*
usf4										8.45		
										(0.12)		
usf4(-1)				0.99		3.95						
				(0.02)		*(0.00)*						
usf4(-6)	-3.49							3.58		3.62		
	(0.01)							*(0.00)*		*(0.08)*		
usf4(-12)				1.69		7.51		3.03		8.98		11.75
				(0.00)		*(0.00)*		*(0.00)*		*(0.18)*		*(0.01)*
MFR	0.72	0.80	0.29	0.35	0.34	0.56	0.23	0.45	0.71	0.86	0.73	0.80
HQ	0.41	0.36	0.68	0.60	1.00	0.72	1.14	0.96	0.24	0.20	0.24	0.21
AIC	0.36	0.30	0.65	0.56	0.96	0.67	1.10	0.88	0.21	0.15	0.21	0.18
BIC	0.48	0.45	0.72	0.67	1.05	0.78	1.20	1.07	0.28	0.27	0.29	0.26

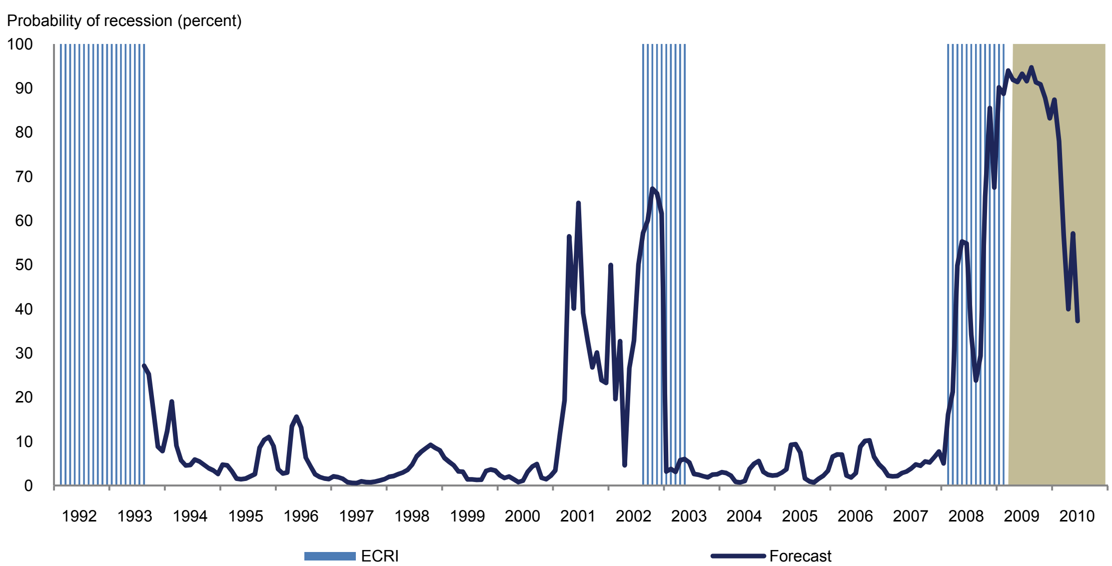
NOTE: For each country, the first column presents the results of the most significant probit model specification given by (2); the second column represents the best model based on (3). P values are in parentheses.

Figure 5: In-Sample and Out-of-Sample Forecasts for Italy Against ECRI Recession Dates



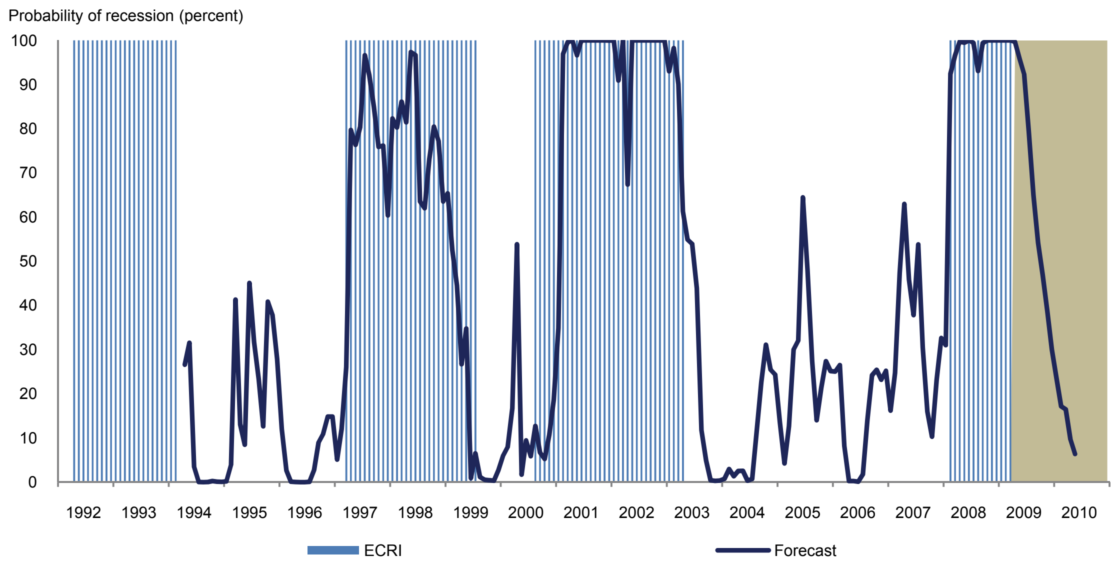
NOTE: The shaded area (right) represents the out-of-sample forecasts.

Figure 6: In-Sample and Out-of-Sample Forecasts for France Against ECRI Recession Dates



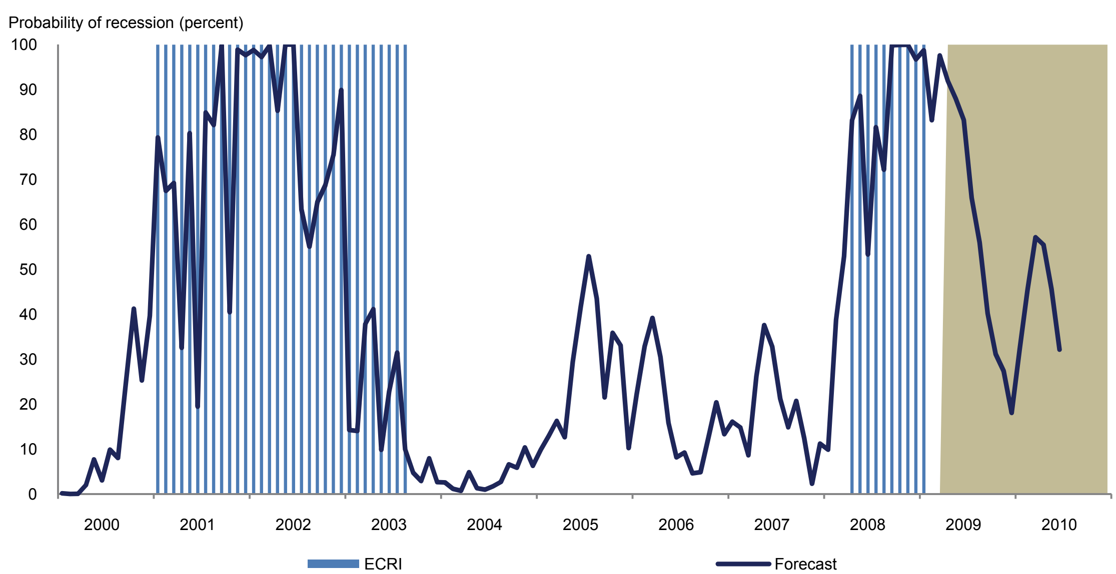
NOTE: The shaded area (right) represents the out-of-sample forecasts.

Figure 7: In-Sample and Out-of-Sample Forecasts for Japan Against ECRI Recession Dates



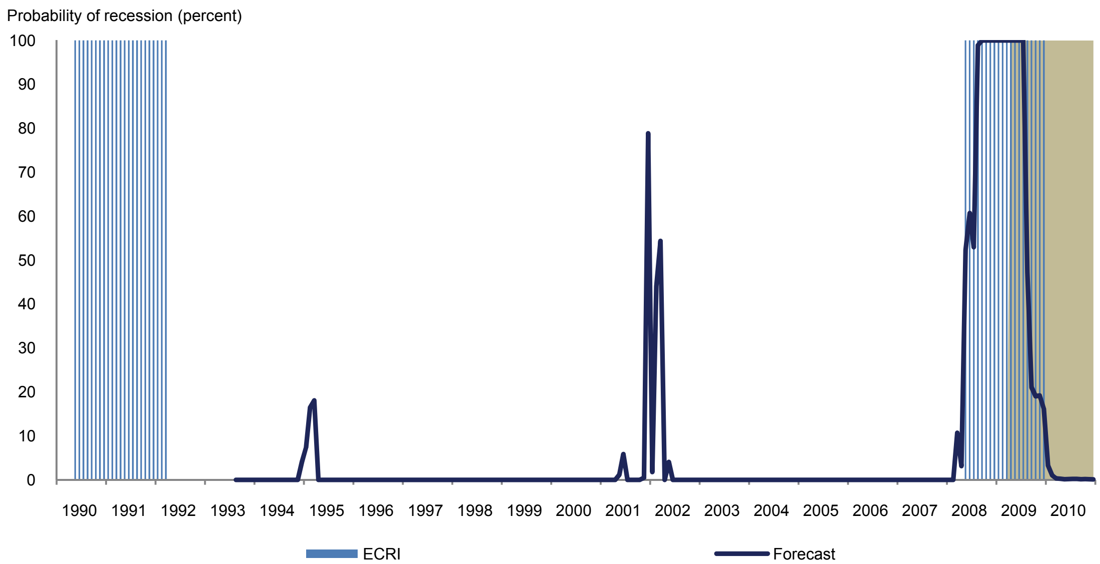
NOTE: The shaded area (right) represents the out-of-sample forecasts.

Figure 8: In-Sample and Out-of-Sample Forecasts for Germany Against ECRI Recession Dates



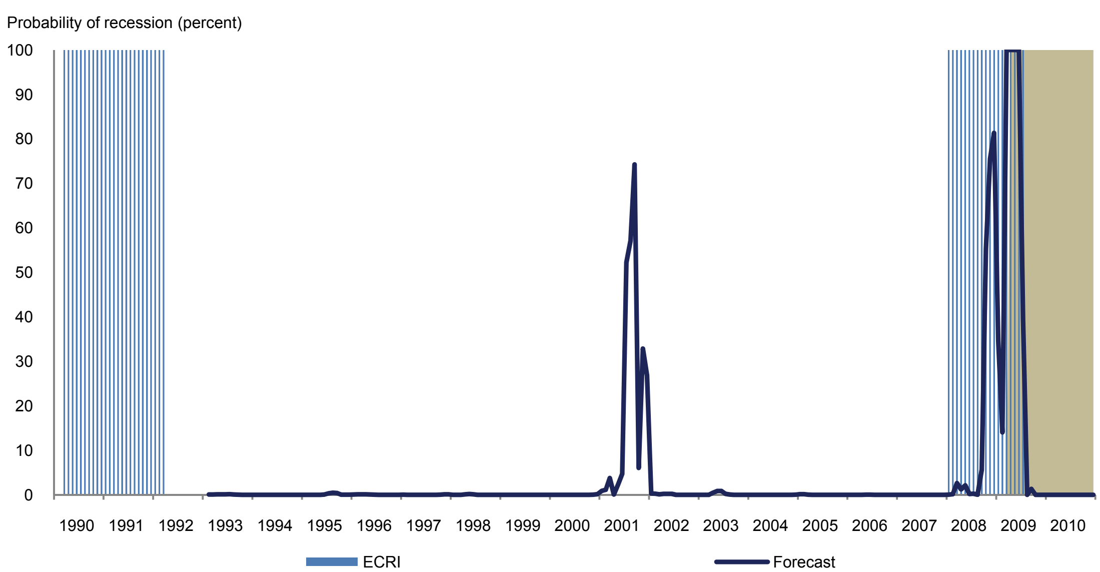
NOTE: The shaded area (right) represents the out-of-sample forecasts.

Figure 9: In-Sample and Out-of-Sample Forecasts for the U.K. Against ECRI Recession Dates



NOTE: The shaded area (right) represents the out-of-sample forecasts.

Figure 10: In-Sample and Out-of-Sample Forecasts for Canada Against ECRI Recession Dates



NOTE: The shaded area (right) represents the out-of-sample forecasts.

(Continued from page 10)

The case of Japan is very interesting because our model clearly depicts the country's last three recessions with remarkable accuracy. While we don't have data before August 1992, the forecast pattern also seems to be consistent with the 1992–93 recession according to ECRI. The out-of-sample forecast's turning point clearly coincides with the end of recession according to ECRI.

The in-sample fit for Germany illustrates the beginning of the country's last two big recessions, with a sharp increase in the probabilities of recession. For the long 2001–03 recession, we observe an apparent turning point around May 2002 that fuels another sharp increase in recession probabilities before the close of the recession. Our model picks up this fact remarkably well. The out-of-sample forecast also coincides with a turning point (end of recession) preceding a sharp decline in the probabilities of recession.

In the U.K., our model picks a false positive in 2001–02 but depicts remarkably well the beginning of the most recent recession. The out-of-sample forecast also presents an accurate path for the end of recession. The case of Canada is very similar to that of the U.K., with a false positive in 2001–02 but a fairly precise description of the most recent recession. Particularly precise is our out-of-sample forecast that detects the end of the Canadian recession.

4. FINDINGS AND POLICY IMPLICATIONS

We looked into the term structure to define a model that represents the NBER recession dates and used this model to forecast the probabilities of recession in the U.S. Our results suggest that the end of the most recent U.S. recession could have been forecast as early as April 2009, when the first green shoots emerged in the U.S. data. The term-structure version we applied proved to be a good predictor of the U.S. real economy, allowing us to signal recessions earlier (and presumably more accurately) than traditional term-structure models do. The U.S. recession indicators produced by our model, which combines the yield spread with forward-looking growth expectations (the output gap growth spread), seem to have significantly preceded those used by most professional forecasters.

Similarly, the model we defined to predict the probabilities of recession in other countries seems to have produced recession indicators earlier than those used by most international forecasters. We find that most of the *a-posteriori* official releases for the countries included in the analysis could have been forecast as early as April 2009. Furthermore, our findings show evidence supporting Fernandez and Nikolsko-Rzhevskyy's 2010 claims that other countries' economic fluctuations are strongly tied to past economic conditions in the U.S.

These results highlight two important issues. First, they add to the evidence of the yield curve as a predictor of economic activity that may be useful to policymakers, market participants, and economic researchers. And second, they corroborate the significance of U.S. economic influence on the rest of the world. Given the lagged U.S. influence, the results also suggest that other countries may benefit from incorporating some U.S. economic indicators or monetary policy decisions into their forecasts.

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