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Do Asset Price Drops Foreshadow Recessions?

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Abstract

This paper examines the usefulness of asset prices in predicting recessions in the G-7 countries. It finds that asset price drops are significantly associated with the beginning of a recession in these countries. In particular, the marginal effect of an equity/house price drop on the likelihood of a new recession can be substantial. Equity price drops are, however, larger and are more frequent than house price drops, making them on average more helpful as recession predictors. These findings are robust to the inclusion of the term-spread, uncertainty, and oil prices. Lastly, there is no evidence of significant bias resulting from the rarity of recession starts.

JEL Classification Numbers: E32; E37; G17

Keywords: Business cycles; Macroeconomic forecasting; Financial markets; Uncertainty; Oil Prices; Binary dependent variable models.

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I. INTRODUCTION

Many observers have noted that asset price drops are often followed by a recession. Historical examples of this regularity include the 1929 stock market crash and the Great Depression; the sharp decline in asset values in 1973-74 and the ensuing economic downturn in the United States and United Kingdom; the early 1990s' asset price collapse and recession in Japan; the stock market downturn in the early 2000's and the 2001 recession in the United States; and the 2008 global crash in asset prices and the Great Recession. The common thread running through these episodes is a steep decline in equity and/or house prices preceding or coinciding with economic downturns of varied intensities. Moreover, many of these asset price collapses cum recessions were accompanied by financial crisis.

Other observers, however, have concluded that asset price declines do not always precede or coincide with economic contractions. The sharp decline in the stock market in 1962, for instance, did little to unsettle the economic recovery process in the United States. Likewise, the stock market crash of October 1987 did not significantly affect economic activity in the United States, despite predictions of a severe recession in 1988. The August 2011 stock market collapse in the United States and Asia was also not followed by a recession in these economies. These observers argue that asset prices (and equity prices, in particular) are poor indicators of forthcoming recessions because they are inherently volatile. Samuelson's (1966) famous epigram that "the stock market has forecast nine of the last five recessions" cleverly summarizes this view.

In this study, we examine whether asset price drops show any link to the starts of recessions in the G-7 countries. Specifically, we assess whether equity and house price drops are reliable predictors of new recessions. Towards this objective, we use a simple binary dependent variable framework (logistic regression) with country fixed effects to predict *new* recessions. In the baseline formulation we introduce five regressors—namely, real equity and house price changes, the term spread, market uncertainty, and the real oil price change. The first two regressors are the variables of interest. The other three regressors capture other cyclical drivers that have featured prominently in the recession forecasting literature.

In the analysis, we explicitly exclude periods where the economy is already in a recession from the estimation sample. This is a key departure from the previous literature, which has tended to pool information across both expansions and recessions, opting to estimate the probability of being in a recession at any given point in time. An important problem with this approach is that it can give a false impression of success in predicting new recessions. In most cases, these studies are reporting the probability of continuing in recession, conditional on the economy already being in recession.

The results indicate that asset prices are significantly related to the beginning of a new recession in the G-7 economies over 1970:Q1-2011:Q4. This finding seems consistent with the literature that emphasizes the association between asset prices and business cycles resulting from the wealth effects that asset price changes have on current and future domestic demand. Moreover, this finding is also in line with the finance literature that states that asset prices contain information about future economic activity. We find evidence that the relationship between asset prices and the starts of new recessions is highly asymmetric—the average marginal effect in the probability of a new recession of a large decline in equity/house prices is much larger in absolute value than that of an equivalent increase. However, large house price drops are relatively uncommon in the period of analysis. This new findings suggests that the early pessimistic assessment on asset prices' ability to help forecast new recessions needs to revised.

There is also evidence that the term spread and market uncertainty can be useful in predicting new recessions. The result on the term spread has been long established in the literature. However, in this study we show that equity price movements have better in-sample forecasting performance. The result on market uncertainty is, to the best of our knowledge, new in the literature. But it is consistent with work that examines the effects of uncertainty on the business cycle, arguing that uncertainty shocks lead to lower growth (Bloom, Kose, and Terrones, 2013). Lastly, oil price changes do not appear to be particularly useful in predicting new recessions.

This paper makes several contributions to the literature. First, we carefully examine the connection between asset prices—both equity prices and housing prices—and new recessions. Previous studies have tended to focus on the chances of being in a recession, rather than the chances of a new recession. They have also typically left out housing prices from the analysis, largely because of data limitations. Second, we explore the effects of uncertainty on the likelihood of a new recession, allowing us to shed additional light on the new evidence and theory arguing that increased market uncertainty can drive recessions. Third, we address the potential biases associated with the fact that new recessions are rare events. In particular, logistic regression will tend to underestimate the probability of rare events in finite samples (King and Zeng, 2001). To assess the severity of the rare-events problem in our study, we therefore investigate the sensitivity of our findings to a number of bias-reducing estimation methods. We show that these biases in our application are, fortunately, not substantial.

The remainder of this paper is structured as follows. In section 2, we present a brief literature review to place our study in perspective. In section 3, we discuss our database and introduce our empirical methodology. In section 4, we report the main findings of this paper. In addition, we examine the robustness of these results. We conclude in section 5 with a brief summary of our main results and discussion of future research.

II. Literature review

Asset prices drops have often been thought to be one of the most important leading indicators of economic downturns. There are good theoretical reasons grounding this view. On the one hand, asset price declines could actually cause a downturn in economic activity by negatively affecting the net wealth, balance sheets, and confidence of households and firms.[2] Asset price declines may also weaken banks' balance sheets, inducing them to raise capital and lower their lending.[3] As a result private sector demand will contract today and in the near future. These effects can be

[2] Recent studies have found that asset price movements that affect households' net wealth are associated with significant changes in household spending (Carroll, Otsuka, and Slacalek, 2011; Case, Quigley, and Shiller, 2013).

[3] These linkages have been formalized by von Peter (2004) and Adrian, Moench, and Shin (2010). A collapse in asset prices can leave financial intermediaries with significant amounts of non-performing loans, as the value of the underlying collateral also collapses.

amplified when financial imperfections are present—through the financial accelerator and related mechanisms—resulting in a larger contraction in economic activity.[4]

An asset price drop could also signal a weakening of the economic outlook to the extent that asset prices are forward-looking. For instance, the basic risk-neutral no-arbitrage pricing equation in finance states that the price of an asset should equal the present discounted expected value of future dividends from the asset.[5] To the extent that dividends and economic conditions move together, stock prices should then be useful in forecasting economic activity. More precisely, if recessions can be foreseen, their onset should be forewarned by the stock markets.

These two elements led many observers to treat asset prices, and equity prices, in particular, as bellwethers of recession. However, early empirical studies found that asset prices were only of limited use to forecast economic downturns.[6] Equity prices, in particular, were prone to producing false positives making them unreliable recession predictors and leading many researchers to seek alternative financial indicators that could be useful to predict economic downturns. Predicting the starts of recessions, however, is an elusive task. New recessions are hard to predict not only because they are rare events, but also because they entail a change in the direction of economic activity. Most business cycle studies utilize a variant of Bry and Boschan's (1971) dating algorithm for cyclical peaks and troughs, where a recession begins in the quarter after a cyclical peak.[7] The identification of these cyclical turning points, however, requires information on the levels of future output. For example, with quarterly data, the dating algorithm incorporates output information from two future quarters.

Influenced by the role played by the collapse in asset prices in the latest global financial crisis, recent studies have, however, revisited the relation between asset price gyrations and business cycles. Barro and Ursua (2009), for instance, study the relationship between stock market crashes and economic depressions for a sample of twenty five economies from 1869 to 2006. They find evidence that the probability of a minor (major) depression conditional on a stock market crash is 30 (11) percent. Thus, stock market crashes provide useful information about the prospects of a depression. Claessens, Kose and Terrones (2012) examine the relationships between business

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[4] See, for instance, Kiyotaki and Moore (1997), Bernanke, Gertler and Gilchrist (1999), and Geanakoplos (2010).

[5] A well-known variant of this, known as the "Gordon equation," named after Myron Gordon, states that if dividends D grow at a constant rate g per period in perpetuity, the equity price P is given by $P=\frac{D(1+g)}{i+\rho-g}$, where i is the risk-free constant interest rate and ρ the constant equity risk premium. To the extent that g, the dividend growth rate, is related to the growth rate of output equity prices would be positively related to future output growth.

[6] Stock and Watson (2003) found that equity prices are generally poor predictors of output growth. In contrast, virtually no study has examined the predictive content of housing prices for economic growth and recessions, reflecting in part data limitations.

[7] Official cyclical peaks and troughs are not available for most advanced countries, necessitating the use of business cycle dating algorithms. Only the euro area and the United States possess such dates which are produced by the Center for Economic Policy Research (CEPR) and the National Bureau of Economic Research (NBER), respectively.

and financial cycles for a large number of countries over the past fifty years. They find that the features of recessions and recoveries are affected by developments in the financial markets. In particular, recessions associated with asset price busts tend to be longer and deeper than other recessions. The association between asset price movements and the beginning of a *new* recession, however, has not been formally examined by this literature.

In addition to asset prices, there is a well established literature that has found that the term spread and oil price movements can be useful at predicting recessions. More recently, the role of market uncertainty as a significant driver of business cycles has been mentioned. We next review the main highlights of these strands of the literature as these variables are included in our benchmark model.

The predictive content of the term spread—the difference between the long- and short-term interest rate—for recessions in the advanced economies has been explored by a number of researchers. For instance, Estrella and Mishkin (1998) examine the performance of the term spread as a predictor of a binary recession indicator in the United States. This relationship is based on the premise that the term spread provides information about the stance of monetary policy and that a tightening in monetary policy, by pushing up short-term real rates and narrowing or even inverting the term spread, can result in a recession. They find that the term spread can indeed play an important role in predicting whether or not the U.S. will be in recession for horizons further than one quarter out. Duarte, Ventis and Paya (2005) find that EMU and U.S. yield spreads are associated with EMU recessions. Christiansen (2013) similarly uses the yield spread to predict simultaneous recessions in several advanced economies.

There is also a growing literature that postulates that uncertainty is an important driver of the business cycle. It has been documented that market uncertainty in the advanced economies is, on average, much higher during recessions than during expansions (Bloom, Kose, and Terrones, 2013).[8] This may be the case because, when faced with high uncertainty, firms reduce their investment demand and delay their projects as they gather new information, as investment can be costly to reverse (Bernanke, 1983, and Dixit and Pindyck, 1994). Similarly, households facing a highly uncertain macroeconomic environment cut their consumption of durable goods as they wait for less uncertain times. Taken together, these mechanisms suggest that high uncertainty may be detrimental to economic activity and lead into recession. This is the first study that explores the association between market uncertainty and the beginning of a new recession.

Lastly, there is some work that highlights a connection between oil price increases and recessions. In particular, it has been noted that when oil prices rise sharply or remain persistently high, recessions have followed in a number of advanced economies. Hamilton (2011b) documents a number of adverse oil supply shock episodes that the United States has experienced since 1859, tracing out their implications for the economy over time. He found that 10 out of the 11 recessions that the U.S. experienced during this period were associated with an increase in oil prices (the exception being the mild recession of 1960-1961). Moreover, 11 of the 12 episodes of

[8] Campbell and others (2001) present early evidence that equity market volatility tends to lead changes in output growth.

oil price increases were associated with a U.S. recession. Engemann, Kliesen, and Owyang (2011) examine whether positive oil price shocks increase the probability of a recession in seven advanced economies over varying sample periods, but all ending in 2009:Q1. They find evidence that, in addition to term spreads, oil price shocks can help predict recessions in these countries. The strength of this relationship, however, varies across countries.

In summary, in this paper we study the relationship between asset price fluctuations and new recessions in the G-7 countries over the past forty years. In contrast with the previous literature, we focus on the starts of recessions, since this information may allow policymakers to put in place timely countercyclical policies and give the private sector sufficient warning to proactively adjust consumption and investment decisions, as well as their portfolio composition. As such, the statistical analysis requires that we omit the quarters-in-recession because they are observed only *after* the event we are interested in predicting has taken place.

III. Data and Methodology

This section introduces the data utilized in the study as well as the empirical framework used in the regression analysis. The database includes information about the cyclical peaks, financial variables, and other controls. The empirical framework is based upon a binary discrete dependent variable model which has been used with some success in earlier work.

A. The Data

Our database comprises quarterly real and financial series for the G-7 countries over the past forty years. The cyclical peaks and troughs for the G-7 economies are obtained from Claessens, Kose, and Terrones (2012). To identify these cyclical turning points, they employ the algorithm introduced by Harding and Pagan (2002), which generalizes the algorithm developed by Bry and Boschan (1971) for the United States. This algorithm first searches for local maxima and minima of the log-level of output (y). It then makes sure that the sequence of identified maxima and minima alternate between peaks and troughs, where an expansion is the period after a trough up to and including a peak, while a recession is the period after a peak up to and including a trough. Furthermore, the identified sequence of peaks and troughs must satisfy censuring rules which require a minimal duration for each phase (expansion or recession) and cycle (a contiguous pair of phases).

Specifically, a peak in quarterly output occurs at time t, if:

$$\{[(y_t - y_{t-2}) > 0, (y_t - y_{t-1}) > 0] \text{ and } [(y_{t+2} - y_t) < 0, (y_{t+1} - y_t) < 0]\}.$$

Note that the algorithm requires output data for two quarters on either side of the peak. According to this rule, a peak at t must be a predecessor to negative growth in the next two quarters. Importantly, this approach is broadly consistent with the observed behavior of the dating committees of the NBER and the CEPR, entities that determine the cyclical turning points of U.S. and the euro area.

The dependent variable in this study is a binary variable that takes on the value of 1 if a country has reached its cyclical peak at *t*, which indicates the end of an expansion, and 0 otherwise. Thus predicting a peak at *t* is equivalent to forecasting that output growth in the next quarter is negative and that output growth in the next two quarters is also negative, conditional on growth previously being positive.

There are two kinds of explanatory variables considered in the study—financial and other. The financial variables include equity prices, house prices, the term spread, the implied or realized volatility of the S&P 500 index (the VXO), the 10-year government bond rate, and the exchange rate. Equity prices are share price indices weighted with the market value of outstanding shares. House prices correspond to indices of house or land prices depending on the country. The term spread is calculated as the difference between the 10-year government bond rate and the 3-month treasury bill rate (or equivalent). The implied or realized volatility of the S&P 500 index comes from Bloom (2009), spliced with the Chicago Board of Options' VXO index from 2006 through 2011. Lastly, the exchange rate is the bilateral, nominal exchange rate of a particular country vis-à-vis the U.S. dollar. Whenever appropriate, these variables have been converted into real terms using the corresponding national consumer price indices. The underlying sources include the IMF's International Finance Statistics, OECD, BIS, Haver Analytics, Bloomberg, Global Financial Database and various country-specific sources.

The other explanatory variables we investigate are oil prices and lagged real GDP growth. Oil prices are the U.S. dollar average petroleum spot prices of West Texas Intermediate, U.K. Brent, and Dubai Fateh crude (equally weighted). This variable comes from the IMF's commodity database and has been converted into constant dollars using the U.S. CPI. Real oil price growth is one of the main variables in our benchmark specification. In addition, we use information on lagged quarterly output growth, which is the best available measure to track economic activity. Lagged output growth from the OECD's Main Economic Indicators is used in the robustness exercises.

B. Methodology

We use a binary discrete dependent variable model based on the logistic function to analyze the relationship between asset price changes and recession starts. As mentioned above, within this framework, we also assess the robustness of our findings to different sets of covariates that have been previously used in the literature.

Let $r_{i,t}$ be a binary recession indicator that takes on two possible values depending on whether the economy is at a cyclical peak or not:

$$r_{i,t} = \begin{Bmatrix} 1, \text{ if economy } i \text{ is in a cyclical peak at time } t \\ 0, \text{ otherwise} \end{Bmatrix}$$

where $i=1,\ldots,N$ indexes the cross-section and $t=1,\ldots,T$ indexes time. Then, assume that the binary response model takes the following form:

$$P\left(r_{i,t}=1\,|\,\mathbf{x}_{i,t},\alpha_i\right)=H\left(\mathbf{x}_{i,t}'\boldsymbol{\beta}+\alpha_i\right)$$

where α_i is a country fixed effect for country i, $\mathbf{x}_{i,t}$ is a K x 1 vector of covariatesfor country i in quarter t, and $\boldsymbol{\beta}$ is K x 1 vector. Moreover, we assume that the function H is the logistic distribution, which implies that:[9,10]

$$H(z)=\Lambda(z)\equiv\exp(z)/[1+\exp(z)],$$

where $z=\mathbf{x}_{i,t}'\boldsymbol{\beta}+\alpha_i$. The unconditional log-likelihood function for this model is then:

$$\ell(\alpha,\boldsymbol{\beta})=\sum_{i=1}^{N}\sum_{t=1}^{T}\{r_{i,t}\ln H(\mathbf{x}_{i,t}'\boldsymbol{\beta}+\alpha_i)+(1-r_{i,t})\ln(1-H(\mathbf{x}_{i,t}'\boldsymbol{\beta}+\alpha_i))\}.$$

In general, there are two approaches to estimating fixed effect logit models, which maximize either the unconditional likelihood function, where the fixed effects are treated as parameters, or the conditional likelihood function, where the other parameters are estimated conditional on the fixed effects. Based on their asymptotic properties, the later is superior to the former. Nevertheless, the unconditional maximum likelihood estimator is much simpler to implement, and always produces estimates of the incidental, fixed effects. Because of this, this method is often preferred by researchers and we use this approach in this paper. Katz (2001) shows that when T is large (i.e., larger than 20) then the estimators behave similarly.

As mentioned before, we consider two key explanatory variables for predicting the beginning of a recession. The first one is the quarterly growth in real equity prices. It is expected that an increase (decrease) in equity prices reduces (raises) the probability of a new recession. The second explanatory variable is the quarterly growth of real house prices. Similar to the case of equity prices, an increase (decrease) in real house prices is expected to reduce (raise) the likelihood of a new recession.

In addition to the two key explanatory variables of interest, we include three important controls in the regression analysis. The first one is the term spread, which is a proxy for the stance of monetary policy. It is expected that a reversal in the term spread is associated with an increase in the probability of a recession. The second control is the implied volatility of equity prices as measured by the VXO, a proxy for market uncertainty. An increase (fall) in this volatility would be expected to increase (reduce) the probability of a new recession. The third control is real oil price growth. An increase in oil prices are expected to raise the probability of a recession

[9] Chen and Tsurumi (2010) use Monte Carlo experiments to help select between probit and logit models for binary variables. They find that if unbalanced binary data is generated by a leptokurtic distribution (highly peaked with fat tails) a logit model is preferable to a probit model.

[10] Note that the logarithm of odds of $r_{i,t.}$ is conveniently linear in the covariates.

across the G-7 countries, as none of these countries is an oil exporter. As noted earlier, these variables have been found to be strongly associated with recessions in other work.

To examine the predictive performance of the logit models, we utilize the receiver operating characteristic curve (ROC).[11] This curve assesses how well these models discriminate between positives (here, a new recession) and negatives (i.e., ongoing expansion), for a classification rule that takes the model's fitted value and compares it to a given cutoff probability. When the fitted probability is above the cutoff, it is classed as a positive (otherwise, a negative). Before explaining how to obtain the ROC, it is important to note that for a given observed state and for a given threshold probability, π, the following identities hold: True positive rate (TP(π)) + False negative rate (FN(π)) = True negative rate (TN(π)) + False positive rate (FP(π)) = 1.[12] A ROC curve portrays the relationship between the true positive rate (TP(π)), that is the proportion of new recessions correctly classified as new recessions, and the false positive rate (FP(π)), which is the proportion of ongoing expansions incorrectly classified as new recessions. The former is typically shown on the y-axis and the later on the x-axis.

ROC curves are monotone increasing functions in the unit square with boundary points (0, 0) and (1, 1). A logit model that is uninformative or has no discrimination ability will generate an ROC curve that coincides with the diagonal 45-degree line (also known as the chance line). The area under the ROC curve (AUC) or *c*-statistic is in this case equal to ½.[13] In contrast, a perfectly informative logit model will generate an ROC that coincides with the left hand and top axis of the unit square, generating an AUC of 1. Note that in this special case, for all π, the true positive rate equals one and the false positive rate equals zero.

In general, one can use the AUC statistic as a global measure of the forecasting performance of different logit models—with the most accurate model showing the largest AUC and the least accurate showing an AUC close to ½. To make the classification using the model operational, some cutoff threshold probability needs to be selected from the large set of possible thresholds characterized by the ROC curve. The selected cutoff could be the optimal threshold from some objective function that would embody the tradeoffs between utility, misclassification costs, efficiency, and so on. Because of its simplicity, in this paper we make use of the Youden index and its associated cutoff threshold π^* (Youden, 1950; Perkins and Schisterman, 2006). Youden's index is defined to be $J = \max\left\{TP\left(\pi^*\right) - FP\left(\pi^*\right)\right\}$, where π^* is then the cutoff threshold that maximizes the capability of the model to correctly discriminate between positives and negatives. Graphically, the Youden index is the maximum vertical distance between the receiver operating characteristic curve and the chance line.

[11] The ROC curve is a graphical method first used for the analysis of radar signals during World War II. Since then, the method has been utilized in many scientific fields including medicine, biomedicine, psychiatry, manufacture production, and more recently economics. See for instance, Zou, O'Malley, and Mauri (2007), Berge and Jordà (2011), and Schularick and Taylor (2012).

[12] The false positive rate is also known as a Type I error while the false negative rate is known as a Type II error.

[13] It is interesting to note that an uninformative logit model has the same predictive power as a coin toss, whose ROC coincides with the 45-degree line.

The estimates of the logit coefficients in rare events analysis are biased in small samples, as the estimated probabilities will tend to be too small. To address the potential bias associated with rare events, we try a number of alternative estimation methods. The first is the bias-reducing penalized likelihood for logit proposed by Firth (1993). This method scales the likelihood function by Jeffrey's (1946) invariant prior for the problem. We also make use of the procedure suggested by King and Zeng (2001) to generate approximately unbiased estimates of logit coefficients and their variance-covariance by correcting for the small sample problem associated with rare events.[14] To achieve this, they introduce prior correction and weighting methods for the logit model. These methods seem most effective when the number of observations is small and the events are rare in the sample (appearing in 5 percent or less of the observations). Finally, we also estimate our baseline specification in the complementary logarithmic framework.[15] This model helps account for the possibility of rare events (a skewed distribution to the left in our case) by adjusting the shape of the likelihood so that it approaches unity as the linear predictor term approaches infinity much more slowly than in the logistic likelihood.

IV. EMPIRICAL RESULTS

We now turn to the analysis of the relationship between asset prices and the starts of recessions in the G-7 countries. We start by presenting some stylized facts about the association between asset prices and recession starts, suggesting that asset prices may have some predictive power for recession starts. Then, we estimate our baseline logistic regression model for the start of recessions, assessing the estimated effects of the explanatory variables and the in-sample forecasting ability of the model. Next, we investigate the robustness of our baseline findings to alternative estimation methods, the inclusion of additional explanatory variables, and the extension of the baseline model with distributed lags. We conclude with a look at the model's out-of-sample performance in predicting the start of the Great Recession by country.

A. A First Look at the Predictive Ability of Financial Asset Prices

We begin by presenting some basic facts about the association between the beginning of recessions and changes in several asset price-related variables. As described in section 3.B, our key dependent variable is a binary indicator for a cyclical peak, which implies that the following quarter is the start of a new recession. Table 1 presents summary statistics for the main covariates we consider in the regression analysis, while Table 2 shows the cyclical peaks and troughs identified by Harding and Pagan's algorithm when applied to quarterly, seasonally-adjusted real GDP for the G-7 over 1970:Q1-2011:Q4. These variables include real equity price growth, real house price growth, the term spread, log implied S&P 500 volatility, and real oil price growth.[16] There is significant variation among the main variables included in the regression

[14] Estimation is performed using the relogit program in Stata. This program, written by King and Zeng, is available http://gking.Harvard.Edu.

[15] The cumulative distribution function for a complementary logarithmic model is given by: $G(z)=1-\exp\{-\exp(z)\}$.

[16] All growth variables are the change in the log level of the relevant series, multiplied by 100.

analysis. In particular, real equity price growth and oil price growth are more volatile than real house price growth and the term spread (as captured by the standard deviation and coefficient of variation). Real house price growth, oil price growth, and equity price volatility are all more skewed to the right, while equity price growth and the term spread are very slightly skewed left (nearly symmetric). Apart from equity price volatility, all of the series are platykurtic, exhibiting fatter tails than the normal distribution. For house and oil price growths, the fat tails are particularly pronounced. An implication of these distributional properties is that equity price drops tend to be larger and more frequent than house price drops.

There is some evidence that in the quarters before a recession, the marginal distributions of financial variables shift, possibly signaling trouble ahead. Figures 1-5 show that equity prices, house prices, and the term spread tend to stall just before the economy moves into a recession, while equity price volatility and oil prices tend to rise. These figures show two empirical frequency distributions of these financial variables, conditional on being in either the year before a new recession or any other time during the expansion phase.[17] As shown, the frequency distribution of equity price growth is left-shifted and displays fatter tails in the quarters before a cyclical peak in output than other times during an expansion (Figure 1). Similarly, the densities of house price growth and the term spread also exhibit leftward shifts and thicker tails just before a new recession (Figures 2 and 3).[18] The term spread result suggests that a tightening in monetary policy may be a trigger of many recessions in the G-7 countries. It is also consistent with earlier findings on the ability of term spread inversions to predict recession starts.

The distribution of the implied volatility of equity prices in the United States also appears to shift prior to recessions, typically moving rightwards (Figure 4). This could reflect either higher global uncertainty pushing economies into downturns or an anticipated recession increasing the uncertainty of profits in the future, and thus equity prices. Similarly, the empirical densities indicate that oil prices tend to rise at a faster pace in the year before a recession than at other times during the expansion phase, with real oil price growth's frequency distribution showing a distinctive rightward shift in the year prior to a new recession (Figure 5). This lends some support to Hamilton's (2011a) observation that high oil prices are often associated with recessions.

Taken together, this exploratory analysis suggests that financial variables and oil price changes may indeed be useful in predicting recession starts as suggested in the literature.

B. Baseline Model

Table 3 shows the regression results for the G-7 sample under various logistic regression model specifications involving the five baseline variables discussed before, plus country-fixed effects

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[17] The empirical densities shown are Epanechnikov kernel-based estimates of the density, pooled across the G-7 sample. The bandwidth used is data-dependent, chosen using Silverman (1986)'s rule-of-thumb.

[18] Nalewaik (2011) reports that output growth show a similar growth pattern in the United States—fast-growth during most of the expansion phase and slow-growth in the last year of the expansion.

and quarterly dummies (to account for any residual seasonality). Columns (1)-(5) show the logit regression coefficients for models based on each of these variables, taken one one-at-a-time. As can be seen, on its own, real equity price growth is highly significant and has the expected sign (negative—so equity price increases reduce the chances of a recession), with an AUC statistic of 0.79, which is significantly above the AUC of a coin toss (0.5).[19] The point estimate indicates that a one percentage point drop in equity prices increase the odds ratio for a new recession by about 12 percent.[20]

House price growth also appears to help protect against recessions (column 2), albeit not statistically significantly. The term spread (column 3) has the expected negative and significant coefficient, indicating that spread inversions raise the estimated chance of a new recession, as reported in previous work. The AUC statistics for both models are significantly above 0.5, but below that of the equity price growth model (significantly below in the case of house price growth).

Log implied S&P volatility shows a large positive and significant relationship to the onset of recessions (column 4). By contrast, real oil price growth exhibits only a small, insignificant positive relationship with recession starts (column 5). In terms of predictive fit, the model with implied S&P volatility has the second highest AUC among the univariate models (only the equity price growth model is higher), while the model with real oil price growth has the lowest.

When real equity and house price growth are jointly included (column 6), the coefficients remain roughly the same size, sign and significance as they are in the single explanatory variable models. However, when the term spread is also included (column 7), real house price growth becomes highly statistically significant. Moreover, its coefficient becomes larger in size. There appears to be additional conditioning information in the term spread that makes the estimate of the coefficient on house prices more precise. The coefficient on the term spread remains similar to the model where it enters alone.

Introducing log implied S&P volatility does not markedly change the coefficients on equity prices, house prices, and the term spread (column 8). However, the coefficient on implied S&P volatility is smaller than that observed in a model where it enters alone as an explanatory variable; the coefficient falls by about 60 percent. However, it remains statistically significant, albeit at the 10 percent level. Our final baseline model, which includes real oil price growth, is shown in column 9. The estimated coefficients and AUC statistic are very similar to those for the model shown in column 8, indicating that the inclusion of oil price growth adds basically no additional information.

The average marginal effects of changes in the different covariates on the predicted probability of a new recession are reported in the last column of the table. For instance, a 1 percentage point

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[19] Some may wonder whether 0.79 is a high AUC statistic. This value exceeds all the AUC values reported by Jordà, Schularick, and Taylor (2011) in their analysis of financial crisis prediction.

[20] Recall that the odds ratio is defined to be $P/(1-P)$, where P is the probability of a new recession. In the logistic regression case, the logarithm of the odds ratio is conveniently linear in the estimated coefficients.

drop in equity or house price growth raises the probability of a new recession by about 0.4 percentage points, while a similarly sized drop in the term spread raises the probability by about 1.2 percentage points. Of course, these are only average marginal effects. Since the model is nonlinear, the actual impact on the predicted probability of a change in an explanatory variable depends upon the levels of all of the explanatory variables.

Figures 6 to 7 graphically illustrate how the predicted probability of a new recession changes with the levels of real equity price growth and real house price growth, for different levels of contributions of the other covariates. These predicted probabilities are overlaid on a histogram showing the distribution of each explanatory variable in the sample. For both real equity price and real house price growths, positive growth only affects the predicted probability at very low levels, implying tiny changes in the absolute level of the predicted probability. By contrast, negative growth is associated with much higher levels of predicted probability. Furthermore, when growth is negative, growth changes can lead to large swings in the predicted probability of a new recession, as evinced by the steeper slope of the curve. Interestingly, the predicted probabilities associated with real equity price and real house price growths are similar in shape and magnitude. However, the variability of real house price growth is much less than that for real equity price growth, as seen by the background histograms in the figures. In practice then, it is real equity price drops that convey the stronger signal that a new recession may be imminent, since large drops are rarely seen in real house prices.

According to the AUC statistic, the baseline model beats any of the single explanatory variable models. In fact, a 90% confidence interval for the AUC statistic of the baseline specification excludes the AUC statistics calculated for the single variable models apart from the models with equity price growth, giving some reassurance that this performance is not a fluke. Interestingly, the AUC statistics from the models which include real equity price growth lie within the 90% confidence interval for the baseline model.

The overall performance of the baseline model (Table 3, column 9) is also illustrated in Figures 8 and 9. As seen in Figure 8, the ROC curve for the baseline is pulled towards the upper left corner, away from the 45 degree line, indicating that the model performs comparatively well in-sample. Similarly, Figure 9 shows that the distribution of in-sample predicted probabilities conditional on a new recession is heavily skewed towards higher probabilities, while the distribution conditional on a continuation of the expansion is peaked near zero. This indicates that the model does a comparatively good job within sample of separating the quarters prior to new recessions from quarters of continuing expansion.

In summary, the analysis in this section finds that equity and house price drops raise the risk of a new recession. This suggests that periods when these asset prices are both falling should be carefully monitored. In addition, because of the rare nature of recessions, there is evidence of asymmetry in the effects of these financial variables, where drops in equity and house prices have much larger effects on the likelihood of recession (raising it) than do favorable rises in price growth.

C. Robustness

To examine the robustness of our findings on the baseline model's in-sample predictive ability, we have undertaken a host of checks, including the use of alternative estimation methods, the addition of other covariates, and the extension to a distributed lag specification.

1. Estimation Method

As discussed earlier, we consider four alternative estimation methods to address the possibility of bias in the estimation: (1) Firth's (1993) bias-corrected maximum likelihood; (2) swapping the complementary log-log transformation for the logistic in the likelihood to account for the skewness in the distribution of events; (3) the small sample and rare event prior corrections for maximum likelihood developed by King and Zeng (2001); and (4) conditional fixed effects maximum likelihood.

As can be seen from Table 4, none of these methods substantially change the estimated coefficients for asset prices and uncertainty from the baseline logit estimates. All of the methods tend to slightly reduce the estimated coefficients across the board, but the overall pattern and signs are unchanged. Log implied equity price volatility, however, is no longer significant when applying Firth's bias correction. The estimates from the conditional fixed effects estimator are also quite similar to the baseline, suggesting that there is no substantive incidental parameters problem in the panel. In terms of their forecasting ability, there is some minor variation in the estimated AUC statistics across methods, with the conditional fixed effects' AUC being slightly lower (although not statistically significantly different).

In summary, the overall message is that the baseline logit results are robust to alternative estimation methods, particularly with regards to the links between asset prices and the beginning of a new recession, three of which are explicitly designed to address possible estimation issues associated with rare events.

2. Additional Explanatory Variables

We also examined how the results change as additional asset-price related variables are included in the baseline model (one-at-a-time). Table 5 shows the results of this exercise for each of the additional variables. The estimated coefficients in the baseline model are very robust to the inclusion of these extra variables, some of which were thought could signal an increased likelihood of a new recession. For instance, the 10-year government bond rate, real GDP growth over the previous quarter, and the rate of nominal exchange rate depreciation versus the U.S. dollar have no significant effects on the probability of a new recession, or on the forecasting ability of the baseline model.

There is some evidence that there are cross-country financial market spillovers affecting a country's chance of a new recession. GDP-weighted real equity price growth in other G-7 economies has a negative and significant effect on the probability of a new recession. The inclusion of this variable reduces the estimated impact of domestic real equity price growth, although it remains statistically significant.

Introducing the period daily standard deviation of daily real equity price growth does not change the point estimates much, but it does make implied S&P volatility insignificant. This is not too surprising, since the two variables are highly related. The standard deviation itself is insignificant. Similarly, adding the quarterly change in the period standard deviation leaves the point estimates essentially unchanged.

The inclusion of very large real equity price drops as an additional regressor also does not change the main baseline results. Inspired by Hamilton (2003)'s work on oil price changes, we constructed the largest net fall in real equity price to be the largest difference between the real equity price in period *t* and its highest level over the previous 180 days (or zero should this be positive). This is meant to explore different non-linearities associated with large drops in asset prices. The net fall in equity prices has a positive but insignificant effect in the associated probability of a new recession. Moreover, the predictive performance of the model does not improve, as the AUC remains unchanged.

As a last check, we allowed for positive and negative equity price growth to have different impacts on the likelihood of a new recession. As seen in the last column of Table 5, it is negative real equity price growth that has the stronger impact. Moreover, it is statistically significant, while that on positive equity price growth is not. However, a test of the equality of the magnitudes of the coefficients fails to reject, indicating that our baseline model, which treats positive and negative equity price growth symmetrically in the logit, is appropriate.

3. Distributed Lags

Finally, we considered how the baseline results change when distributed lags in the different covariates are included. In addition to the contemporaneous values, we include up to 3 lags per covariate to keep the lag structure reasonable. Initially, we include the lags in the single variable models and end by adding them to the baseline model.

Table 6 shows the results of these exercises. Column 1 shows that equity price growth maintains its size and statistical significance relative to the values observed in the baseline regression. Similar to Table 3, when real house price growth is considered on its own, none of the terms are statistically significant, although there is negative contemporaneous point estimate (column 2). The negative effect of the term spread changes in its timing, with the first lag being more important than the contemporaneous term, both in magnitude and statistical significance (column 3). In fact, although statistically insignificant, the coefficient on the contemporaneous term becomes perplexingly positive, indicating that contemporaneous yield curve inversions actually indicate a lower chance of a recession start, at least in the next quarter. However, the sum of the coefficients on the contemporaneous and first lag terms for the term spread is about the same size and sign as that of the single coefficient on the term spread in the baseline model.

Log implied S&P volatility shows an even larger and significant contemporaneous impact on the probability of a new recession (column 4). The lag terms have negative signs, indicating that making it past a period of high volatility without tipping into recession reduces the likelihood that a recession starts. However, these coefficients are statistically insignificant.

Unlike the baseline model, real oil price growth does start to show some significant impact in the distributed lag specification (column 5). In particular, its first and second lags show positive and statistically significant effects on the probability of a new recession. Thus, increases in oil prices in the recent past increase the risk of a new recession with a short lag.

If all the baseline variables and their lags are included simultaneously (column 6), the overall picture remains broadly in line with those of the baseline regression from the last column of Table 3. The coefficient on equity price growth is negative, significant, and of similar, but slightly smaller, magnitude to the one obtained in the baseline regression. The first lag of equity price growth is also negative and significant (at the 10 percent level), but with a smaller coefficient than the contemporaneous term. The coefficient on real house price growth is significant and slightly larger than in the baseline regression suggesting a stronger effect of house price changes on the probability of a new recession. The adverse impact of a negative term spread appears to bite only with a lag, similar to column 3 where it was introduced on its own.

In summary, the inclusion of distributed lags of the covariates of the baseline model does not substantially alter our main findings related to asset prices reported earlier. These exercises, however, do highlight some fragility of the results associated with house prices and the term spread. Moreover, real oil price growth only weighs on the economy with a lag.

V. Out-of-Sample Model Evaluation

How does the baseline model perform on an out-of-sample basis? To address this question, we consider the performance of the model over an expanding window starting in 2005:Q4 and ending in 2011:Q4. This period covers the run-up to the Great Recession and the recovery from this recession. It is interesting to note that some of the G-7 economies have experienced 2 recessions in this period.

At each quarter, we make a one-step ahead recession prediction from the model. The out-of-sample receiver operating characteristic curve performs well over the period since 2006:Q1, with an AUC of 0.71. Zooming in to the start of the Great Recession by country (Figure 10), we can see how the predictions vary across countries. The baseline model does well at calling the recession start in France, Germany, Italy, Japan, the United Kingdom, and the United States, with the prediction exceeding the optimal Youden classification threshold. It performs poorly for Canada. Moreover, the United States classification of 2007:Q4 as the start of a new recession is a close call, with the predicted probability just above the optimal threshold.

VI. Conclusion

In this paper, we examined the usefulness of asset prices—equity prices and house prices—in predicting new recessions in the G-7 countries over the past forty years. Our focus on the starts of recessions differs from much of the literature, which has tended to pool recession starts and periods of ongoing recession. The analysis suggests that asset price drops are significantly associated with the start of a recession in these countries. In particular, the marginal effect of an equity/price drop on the likelihood of a new recession can be substantial. As large equity price drops are observed with higher frequency than large house price drops, this reinforces the view that equity prices are particularly useful predictors of recessions.

These findings hold even when the term spread, which has been reported to be one of the best predictors of recessions in the advanced economies, market uncertainty, and real oil price growth are included as explanatory variables. While confirming the usefulness of the term spread, there is new evidence that market uncertainty can also help predict recessions. In contrast, oil price movements do not seem to be useful predictors of economic contractions. Moreover, there is evidence that changes in equity price have better in-sample forecasting performance than many of the other commonly featured recession predictors, including the term spread.

We find no evidence of significant bias resulting from the fact that new recessions are rare events. An important concern in studies of rare events is downward bias, which could be severe in small samples. To address this concern we examined the sensitivity of our findings to a number of bias-reducing estimation methods finding no evidence of significant problems.

Going forward, we would like to extend our analysis to all the advanced economies. This is not just an intellectual exercise but, more importantly, the development of such a framework may help policymakers to straight-forwardly assess the risks of a new recession both in their own countries as well as in their financing and trading partners. In addition, we would like to study further the role of market uncertainty in predicting recessions in the advanced economies by exploring different measures of uncertainty and by examining the extent to which market uncertainty and asset price drops are interlinked.

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Table 1. Summary Statistics for the G-7

1970:Q1-2011:Q4

Variable	Mean	Standard Deviation	Coefficient of Variation	Median	1st Quartile	3rd Quartile	Maximum	Minimum	Coefficient of Skewness	Coefficient of Kurtosis
Real Equity Price Growth	0.81	7.934	9.795	1.2	-3.279	5.691	33.29	-29.63	-0.38	4.617
Real House Price Growth	0.617	2.204	3.571	0.482	-0.531	1.49	15.51	-9.829	1.134	10.58
Term Spread	1.453	1.788	1.23	1.565	0.34	2.61	6.393	-7.09	-0.44	4.2
Log Implied/Realized S&P Volatility	2.946	0.279	0.0947	2.924	2.747	3.132	3.784	2.36	0.293	2.808
Real Oil Price Growth	1.852	15.5	8.368	0.503	-3.518	7.454	134	-49.47	3.074	30.66
10 Year Government Bond Yield	7.607	3.148	0.414	7.353	5.033	9.21	21.21	2.047	0.828	3.688
Real GDP Growth (seasonally adjusted)	0.789	0.715	0.905	0.727	0.363	1.129	5.057	-3.518	0.633	7.505
Rate of Exchange Rate Depreciation versus USD	-0.215	3.938	-18.31	0	-2.206	1.728	18.76	-14.18	0.202	4.391
GDP-Weighted Real Equity Price Growth in other G-7	0.808	8.263	10.22	0.777	-2.106	3.884	35.75	-64.06	-0.582	11.79
GDP-Weighted Negative Real Equity Price Growth in other G-7	-2.235	5.177	-2.316	0	-2.106	0	0	-64.06	-4.914	42.13
Standard Deviation of Daily Real Equity Price Growth	0.814	0.386	0.475	0.712	0.55	0.965	3.22	0.255	1.779	7.739
Change in the Standard Deviation of Daily Real Equity Price Growth	0.0136	0.371	27.38	-0.0141	-0.169	0.154	2.474	-2.017	0.606	9.724
Largest Net Fall in Real Equity Price over past 180 days (percent)	-0.863	1.771	-2.052	0	-1.167	0	0	-22.91	-4.022	33.26
Negative Real Equity Price Growth	-2.572	4.854	-1.887	0	-3.279	0	0	-29.63	-2.593	10.58
Positive Real Equity Price Growth	3.382	4.688	1.386	1.2	0	5.691	33.29	0	1.914	7.7
Estimation Sample Size	945	945	945	945	945	945	945	945	945	945

Note: All growth rates and the rate of exchange rate depreciation are calculated on a quarter-to-quarter basis. Growth rates are log differences times 100. The underlying real equity price, real oil price, real house price, real GDP, or nominal exchange rate versus the USD is the quarterly average level of the indicated variable. The coefficient of variation is the ratio of the mean to the standard deviation. A negative coefficient of skewness indicates that the underlying distribution of the variable has a relatively longer left-tail, while a positive coefficient indicates a relatively longer-right tail. A coefficient of kurtosis greater than 3 indicates that the underlying distributions exhibits a greater degree of peakedness and has fatter tails than a normal distribution. Conversely, a coefficient less than 3 indicates that the underlying distribution exhibits less peakedness and more of a plateau with thinner tails than a normal distribution.

Table 2. Peaks and Troughs in the G-7
1970:Q1-2011:Q4

Country	Trough	Peak
United States	1970:Q4	1973:Q4
	1975:Q1	1980:Q1
	1980:Q3	1981:Q3
	1982:Q3	1990:Q3
	1991:Q1	2000:Q4
	2001:Q3	2007:Q3
	2009:Q2	
United Kingdom		1973:Q2
	1974:Q1	1974:Q3
	1975:Q3	1979:Q2
	1981:Q1	1990:Q2
	1991:Q3	2008:Q1
	2009:Q3	
France		1974:Q3
	1975:Q1	1980:Q1
	1980:Q4	1992:Q1
	1993:Q3	2002:Q3
	2003:Q2	2008:Q1
	2009:Q1	
Germany		1974:Q1
	1975:Q1	1980:Q1
	1980:Q4	1981:Q3
	1982:Q4	1992:Q1
	1993:Q1	1995:Q3
	1996:Q1	2002:Q3
	2003:Q2	2004:Q1
	2004:Q3	2008:Q1
	2009:Q1	
Italy		1974:Q3
	1975:Q2	1977:Q1
	1977:Q3	1981:Q4
	1982:Q4	1992:Q1
	1993:Q3	1996:Q1
	1996:Q4	2001:Q1
	2001:Q4	2002:Q4
	2003:Q2	2004:Q3
	2005:Q1	2008:Q1
	2009:Q2	2011:Q2
Canada		1980:Q1
	1980:Q3	1981:Q2
	1982:Q4	1990:Q1
	1991:Q1	2007:Q4
	2009:Q2	2011:Q1
Japan		1993:Q1
	1993:Q4	1997:Q1
	1999:Q1	2001:Q1
	2001:Q4	2008:Q1
	2009:Q1	2010:Q3
	2011:Q2	

Note: Peaks and troughs are identified using the Bry-Boschan/Harding-Pagan algorithm, applied to quarterly, seasonally-adjusted real GDP for each country.

Table 3. Explaining Recession Starts in the G-7

Baseline Results, 1970:Q1-2011:Q4

	Logistic Regression Model									
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Aver. Marg. Eff.
Real Equity Price Growth	-0.124***					-0.125***	-0.120***	-0.102***	-0.102***	-0.00384***
	(0.0216)					(0.0220)	(0.0256)	(0.0282)	(0.0293)	(0.0010)
Real House Price Growth		-0.0875				-0.0819	-0.106***	-0.115***	-0.116***	-0.00437***
		(0.0727)				(0.0513)	(0.0391)	(0.0437)	(0.0442)	(0.0015)
Term Spread			-0.360**				-0.316**	-0.317**	-0.317**	-0.0119**
			(0.1440)				(0.1450)	(0.1510)	(0.1500)	(0.0053)
Log Implied/Realized S&P Volatility				2.377***				0.963*	0.970*	0.0365*
				(0.4460)				(0.5030)	(0.5110)	(0.0186)
Real Oil Price Growth					0.00243				0.00084	0.00003
					(0.0070)				(0.0064)	(0.0002)
Observations	945	945	945	945	945	945	945	945	945	
Pseudo R-squared	0.18	0.0672	0.105	0.113	0.0628	0.185	0.217	0.223	0.223	
Number of Cases	44	44	44	44	44	44	44	44	44	
Log-Likelihood	-145.8	-166	-159.2	-157.8	-166.7	-145.1	-139.3	-138.2	-138.2	
AUC	0.794	0.71	0.739	0.763	0.691	0.799	0.819	0.825	0.825	
90% LB for AUC	0.736	0.64	0.672	0.702	0.626	0.74	0.759	0.765	0.765	
90% UB for AUC	0.853	0.779	0.805	0.824	0.757	0.858	0.879	0.885	0.885	
Optimal Youden Cutoff	0.0374	0.0492	0.0356	0.0684	0.0491	0.0405	0.0619	0.0674	0.068	
True Positive Rate (Percent)	75	68.18	81.82	59.09	63.64	75	72.73	70.45	68.18	
False Positive Rate (Percent)	31.41	31.41	42.18	18.65	30.85	28.75	17.76	14.98	14.65	

Note: The dependent variable is the Bry-Boschan/Harding-Pagan algorithm identified peak for seasonally adjusted, quarterly real GDP growth, conditional on being in an expansion. Heteroskedasticity and autocorrelation-within-country robust standard errors are in parentheses underneath the coefficient estimate. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Shown only for model (9), the average marginal effects show the average impact of a one-unit change in the explanatory variables on the probability of a new recession. Growth rates are log differences times 100. All models include country-specific intercepts and quarterly dummies.

Table 4. Explaining Recession Starts in the G-7

Robustness to Estimation Method, 1970:Q1-2011:Q4

	Estimation Method				
Explanatory Variable	Baseline	Firth's Bias Correction	Complementary Log-Log	King and Zeng's Correction	Conditional Fixed Effects
Real Equity Price Growth	-0.102***	-0.0971***	-0.0979***	-0.0971***	-0.0999***
	(0.0293)	(0.0227)	(0.0266)	(0.0214)	(0.0231)
Real House Price Growth	-0.116***	-0.108*	-0.0985**	-0.108*	-0.113*
	(0.0442)	(0.0644)	(0.0415)	(0.0585)	(0.0652)
Term Spread	-0.317**	-0.304***	-0.283**	-0.304***	-0.311***
	(0.1500)	(0.0916)	(0.1260)	(0.1010)	(0.0935)
Log Implied/Realized S&P Volatility	0.970*	0.945	0.906*	0.947*	0.951
	(0.5110)	(0.6450)	(0.5040)	(0.5170)	(0.6570)
Real Oil Price Growth	0.0008	0.0016	0.0009	0.0017	0.0008
	(0.0064)	(0.0067)	(0.0058)	(0.0066)	(0.0070)
Observations	945	945	945	945	945
Log-Likelihood	-138.2	-115.5	-137.7		-126.1
AUC	0.825	0.825	0.822	0.825	0.802
90% LB for AUC	0.765	0.766	0.762	0.766	0.736
90% UB for AUC	0.885	0.884	0.882	0.884	0.868

Note: The dependent variable is the Bry-Boschan/Harding-Pagan algorithm identified peak for seasonally adjusted, quarterly real GDP growth, conditional on being in an expansion. Standard errors are in parentheses underneath the coefficient estimate. For the baseline and complementary log-log estimation methods, these are heteroskedasticity and autocorrelation-within-country robust. King and Zeng's correction does not output the log-likelihood, so none is shown. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Growth rates are log differences times 100. All models include country-specific intercepts and quarterly dummies.

Table 5. Explaining Recession Starts in the G-7

Robustness to Additional Explanatory Variables, 1970:Q1-2011:Q4

	Logistic Regression Model							
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real Equity Price Growth	-0.102***	-0.102***	-0.0997***	-0.0692**	-0.0996***	-0.0950***	-0.108***	
	(0.0313)	(0.0304)	(0.0308)	(0.0324)	(0.0342)	(0.0352)	(0.0369)	
Real House Price Growth	-0.115***	-0.109**	-0.125***	-0.114**	-0.115***	-0.116**	-0.116***	-0.116***
	(0.0347)	(0.0443)	(0.0425)	(0.0458)	(0.0432)	(0.0463)	(0.0435)	(0.0446)
Term Spread	-0.316**	-0.326**	-0.325**	-0.327**	-0.321*	-0.324**	-0.314**	-0.317**
	(0.1390)	(0.1460)	(0.1420)	(0.1500)	(0.1690)	(0.1640)	(0.1550)	(0.1540)
Log Implied/Realized S&P	0.974	0.935*	0.942*	0.892*	0.9	0.928**	1.021**	0.914*
Volatility	(0.6150)	(0.4910)	(0.5390)	(0.4570)	(0.6180)	(0.4460)	(0.4890)	(0.5120)
Real Oil Price Growth	0.000836	0.0014	0.00213	0.000412	0.000959	0.00113	0.000397	0.00113
	(0.0065)	(0.0064)	(0.0065)	(0.0064)	(0.0061)	(0.0063)	(0.0069)	(0.0066)
10 Year Government Bond Yield	0.00189							
	(0.0754)							
Real GDP Growth (seasonally		-0.319						
adjusted)		(0.4270)						
Rate of Exchange Rate			-0.0435					
Depreciation versus USD			(0.0557)					
GDP-Weighted Real Equity Price				-0.0423***				
Growth in other G-7				(0.0162)				
Standard Deviation of Daily Real					0.101			
Equity Price Growth					(0.7540)			
Change in the Standard Deviation						0.307		
of Daily Real Equity Price Growth						(0.5600)		
Largest Net Fall in Real Equity							0.0332	
Price past 180 days (percent)							0.0752	
Negative Real Equity Price Growth								-0.110***
								0.0352
Positive Real Equity Price Growth								-0.083
								(0.0660)
Observations	945	945	945	945	945	945	945	945
Pseudo R-squared	0.223	0.228	0.226	0.23	0.223	0.225	0.223	0.223
Log-Likelihood	-138.2	-137.3	-137.7	-136.9	-138.2	-137.9	-138.2	-138.2
AUC	0.825	0.827	0.832	0.833	0.825	0.824	0.825	0.825
90% LB for AUC	0.765	0.765	0.775	0.775	0.765	0.765	0.765	0.765
90% UB for AUC	0.884	0.889	0.888	0.891	0.885	0.884	0.885	0.884
Optimal Youden Cutoff	0.068	0.060	0.046	0.059	0.069	0.075	0.071	0.061
True Positive Rate (Percent)	68.18	72.73	77.27	75	70.45	65.91	70.45	70.45
False Positive Rate (Percent)	14.87	15.98	22.97	16.87	14.32	12.65	13.87	16.87

Note: The dependent variable is the Bry-Boschan/Harding-Pagan algorithm identified peak for seasonally adjusted, quarterly real GDP growth, conditional on being in an expansion. Heteroskedasticity and autocorrelation-within-country robust standard errors are in parentheses underneath the coefficient estimate. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Growth rates are log differences times 100. All models include country-specific intercepts and quarterly dummies.

Table 6. Explaining Recession Starts in the G-7

Robustness to Distributed Lags, 1970:Q1-2011:Q4

	Logistic Regression Model					
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Real Equity Price Growth	-0.113***					-0.0808**
	(0.0199)					(0.0319)
Lag 1 of Real Equity Price Growth	-0.0398					-0.0569*
	(0.0303)					(0.0315)
Lag 2 of Real Equity Price Growth	-0.0271					-0.0228
	(0.0324)					(0.0404)
Lag 3 of Real Equity Price Growth	0.00767					0.00783
	(0.0145)					(0.0121)
Real House Price Growth		-0.153				-0.128***
		(0.1070)				(0.0483)
Lag 1 of Real House Price Growth		0.111				0.0798
		(0.1180)				(0.1250)
Lag 2 of Real House Price Growth		-0.0463				-0.142
		(0.1200)				(0.0888)
Lag 3 of Real House Price Growth		0.103				0.0542
		(0.1230)				(0.1120)
Term Spread			0.29			0.404***
			(0.2060)			(0.1360)
Lag 1 of Term Spread			-0.740**			-0.797*
			(0.3510)			(0.4180)
Lag 2 of Term Spread			-0.0758			-0.232
			(0.1810)			(0.3210)
Lag 3 of Term Spread			0.0667			0.221
			(0.1600)			(0.1690)
Log Implied/Realized S&P Volatility				4.502***		3.061***
				(0.7660)		(1.1780)
Lag 1 of Log Implied/Realized S&P Volatility				-1.437		-2.164
				(0.9350)		(1.5270)
Lag 2 of Log Implied/Realized S&P Volatility				-1.138		-0.935
				(1.2710)		(0.9990)
Lag 3 of Log Implied/Realized S&P Volatility				-0.962		-0.724
				(1.0500)		(1.1450)
Real Oil Price Growth					0.00483	0.00139
					(0.0059)	(0.0084)
Lag 1 of Real Oil Price Growth					0.0150***	0.0108*
					(0.0043)	(0.0058)
Lag 2 of Real Oil Price Growth					0.0283***	0.0107
					(0.0073)	(0.0084)
Lag 3 of Real Oil Price Growth					0.0104	0.00114
					(0.0075)	(0.0040)
Observations	915	915	915	915	915	915
Pseudo R-squared	0.2	0.0751	0.141	0.154	0.116	0.323
Log-Likelihood	-141.2	-163.2	-151.6	-149.2	-156	-119.4
AUC	0.815	0.73	0.761	0.791	0.75	0.871
90% LB for AUC	0.762	0.67	0.695	0.731	0.688	0.82
90% UB for AUC	0.869	0.789	0.827	0.851	0.813	0.921
Optimal Youden Cutoff	0.033	0.037	0.065	0.034	0.055	0.111
True Positive Rate (Percent)	79.55	79.55	54.55	79.55	61.36	50.00
False Positive Rate (Percent)	35.71	48.11	20.21	42.71	30.77	7.69

Note: The dependent variable is the Bry-Boschan/Harding-Pagan algorithm identified peak for seasonally adjusted, quarterly real GDP growth, conditional on being in an expansion. Heteroskedasticity and autocorrelation-within-country robust standard errors are in parentheses underneath the coefficient estimate. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Growth rates are log differences times 100. All models include country-specific intercepts and quarterly dummies.

Figure 1:

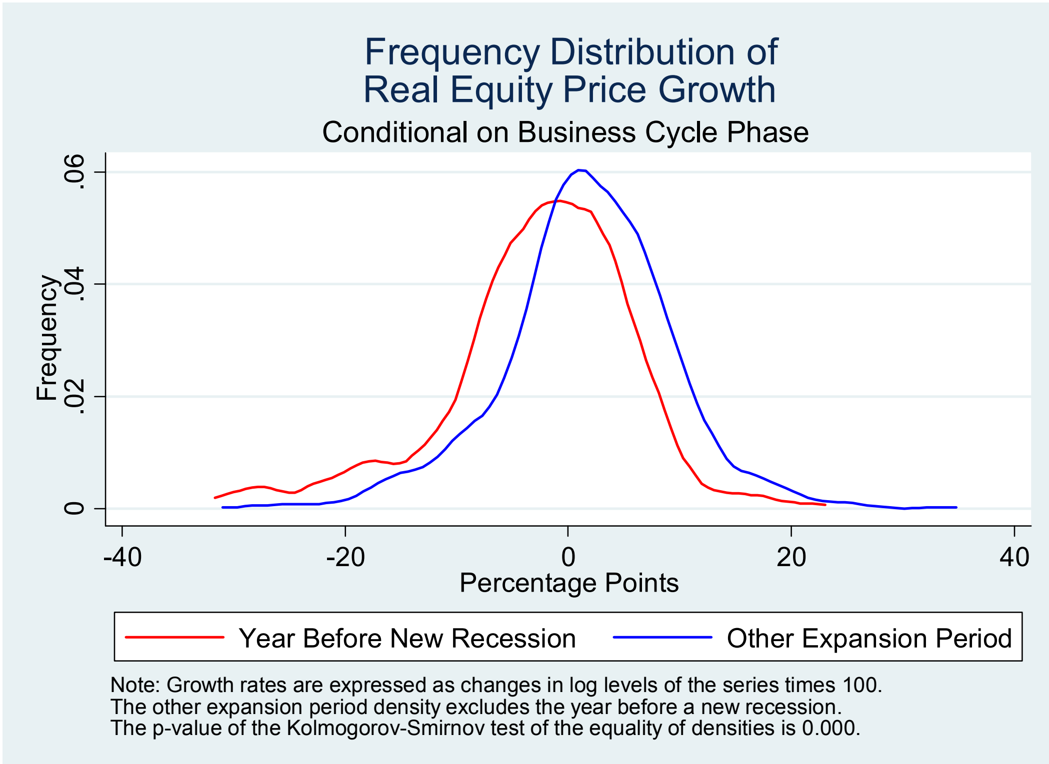


Figure 2:

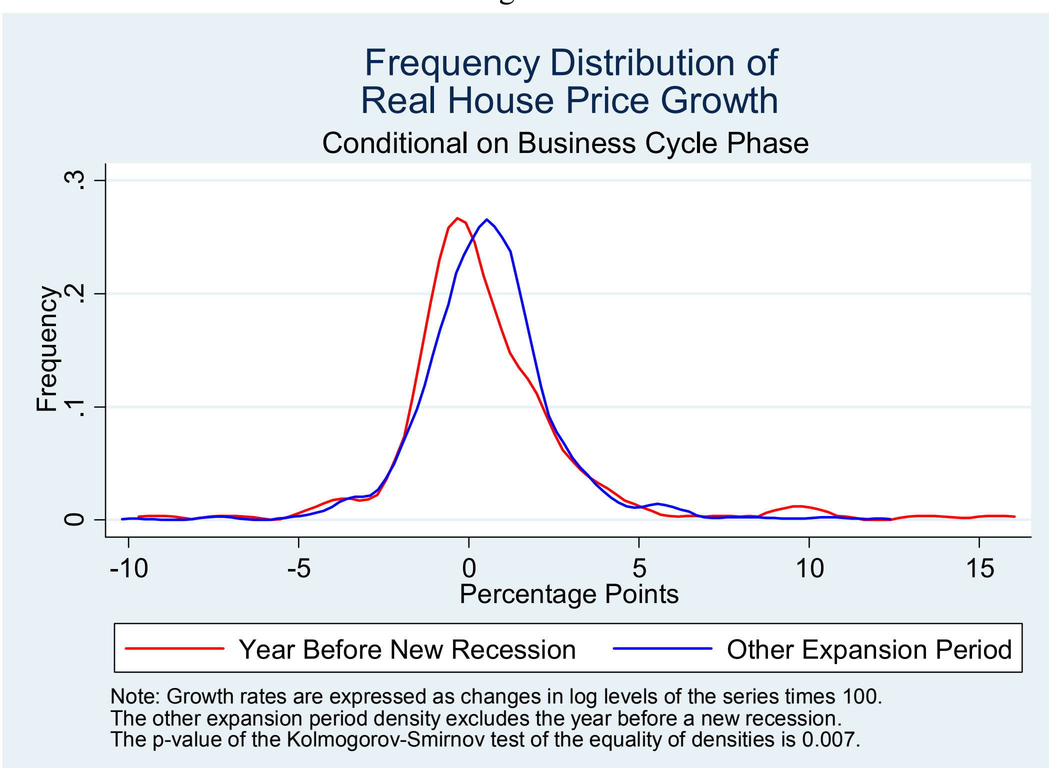


Figure 3:

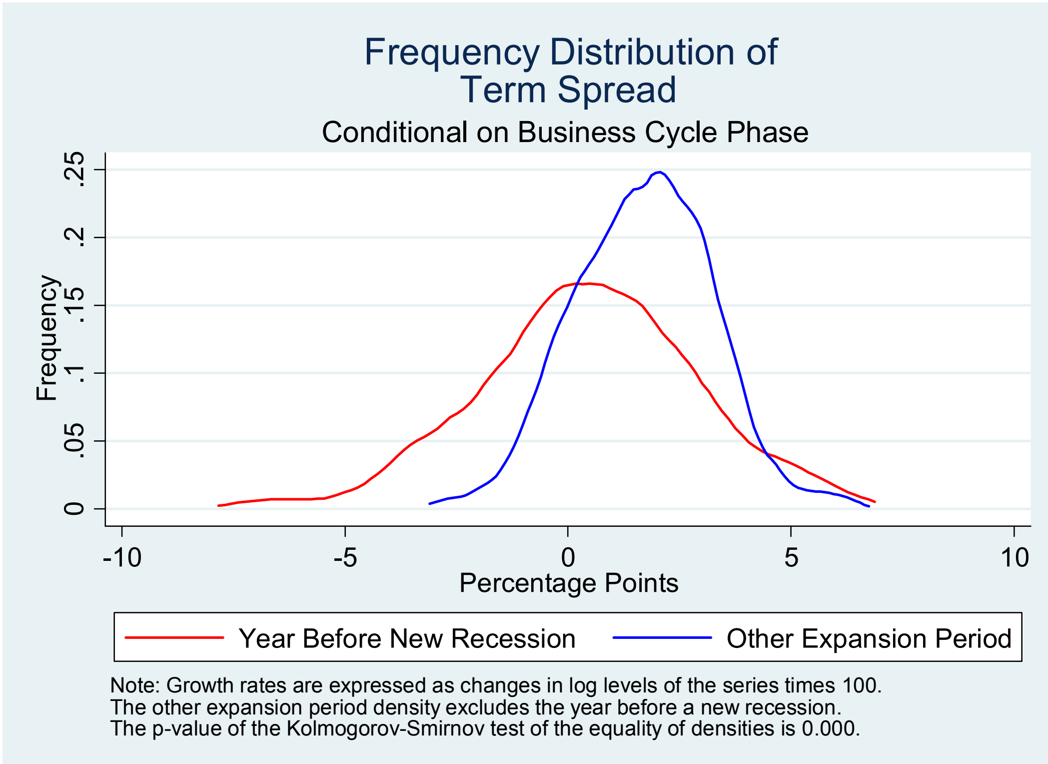


Figure 4:

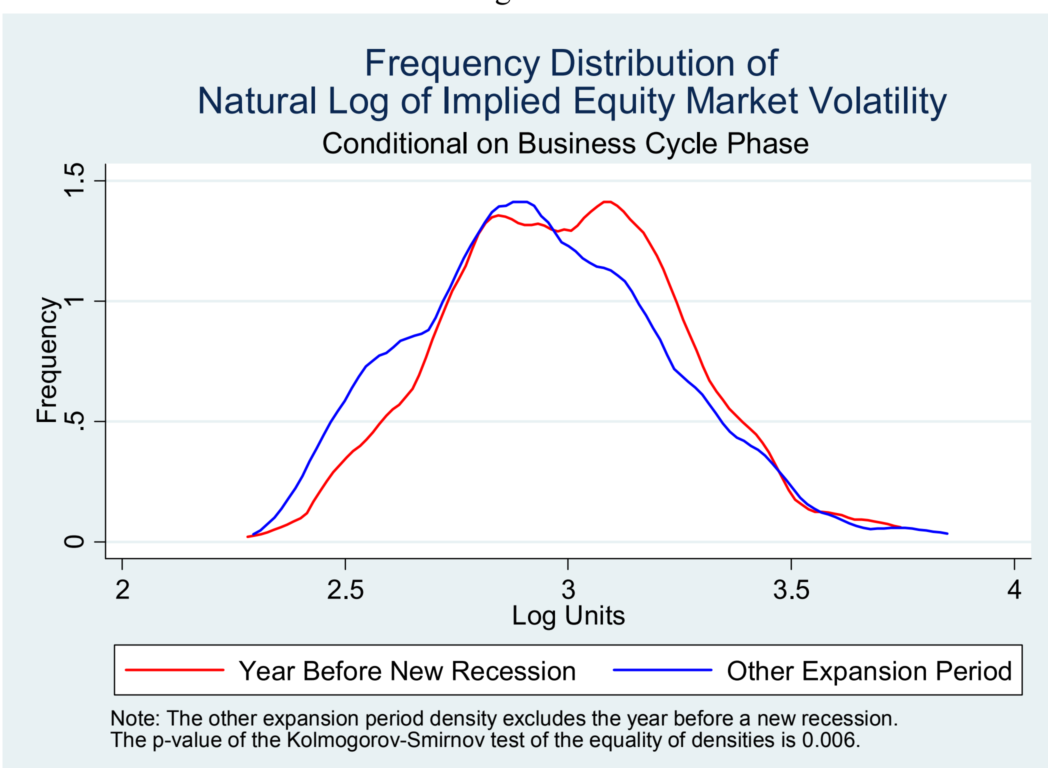


Figure 5:

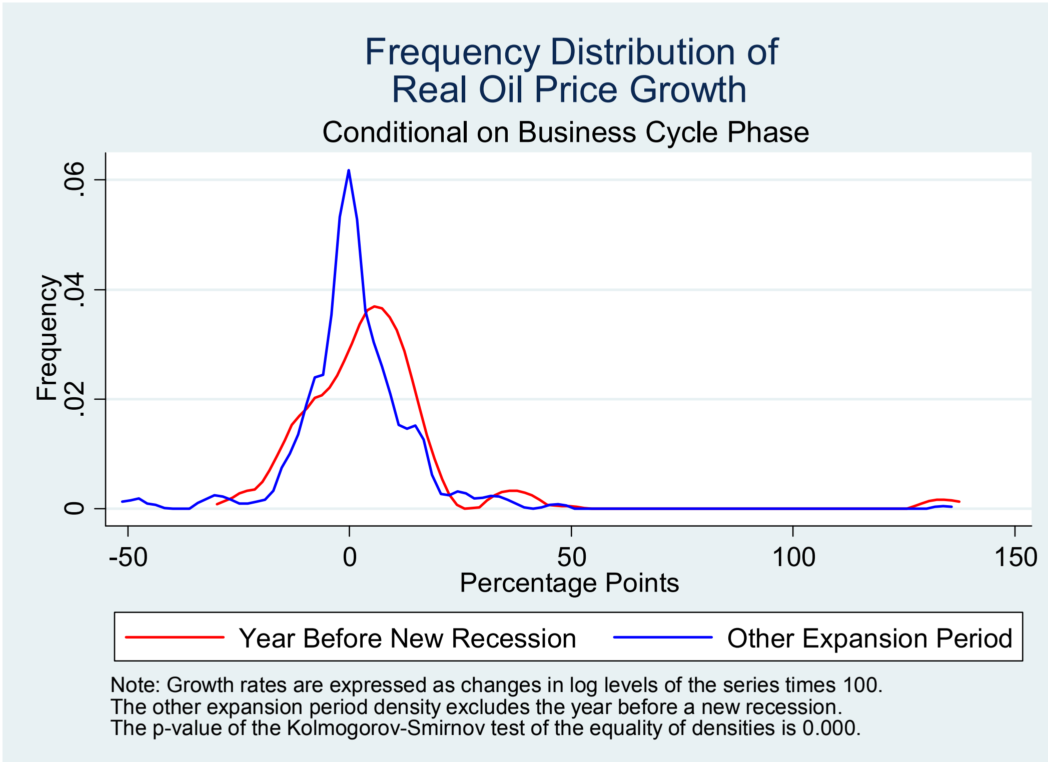
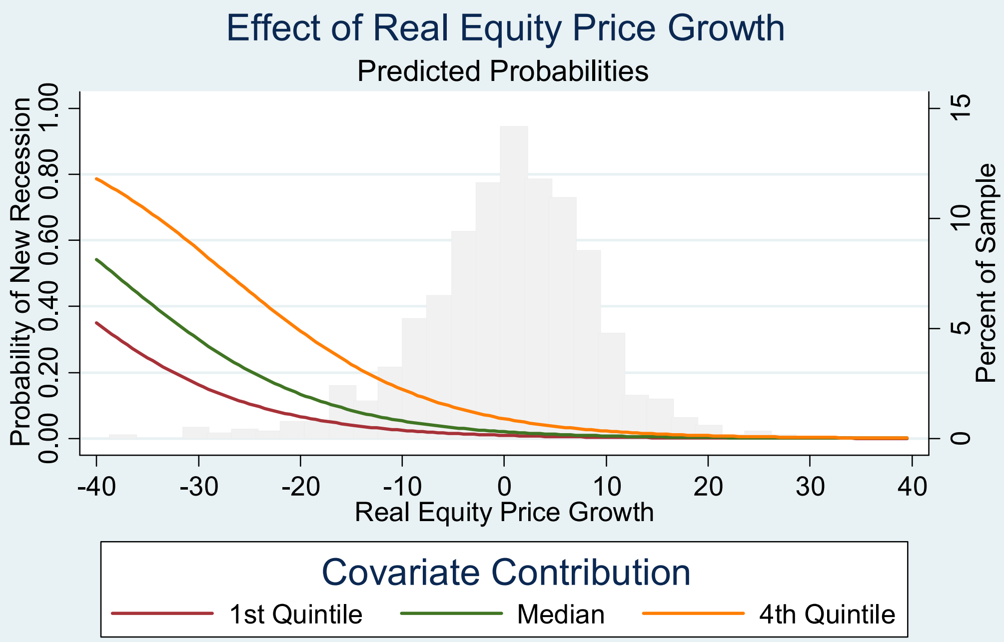
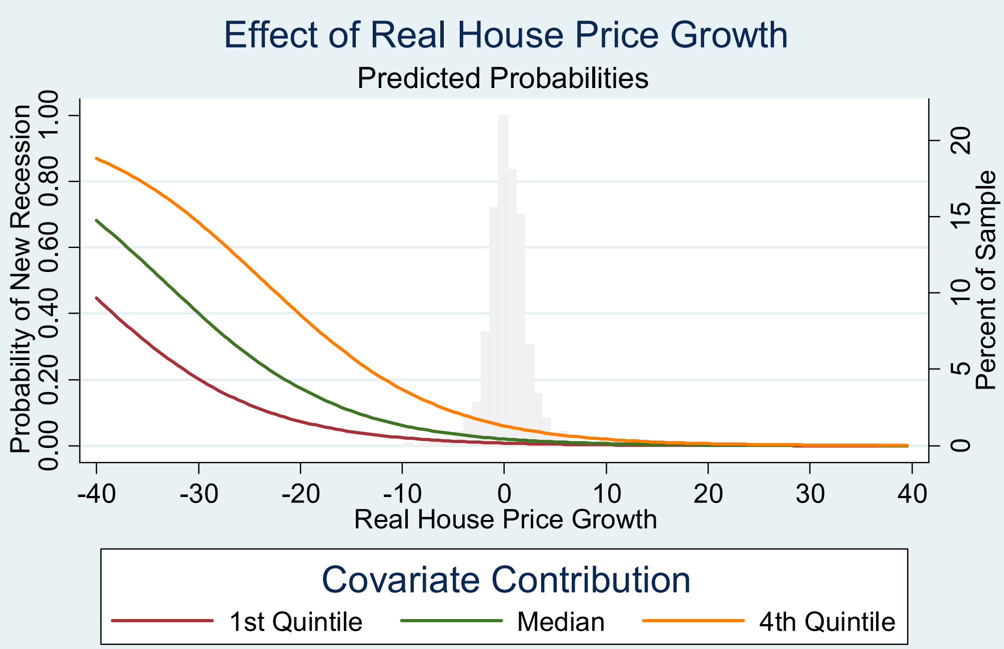

Frequency Distribution of
Real Oil Price Growth
Conditional on Business Cycle Phase
Frequency
0
.02
.04
.06
-50
0
50
100
150
Percentage Points
Year Before New Recession
Other Expansion Period
Note: Growth rates are expressed as changes in log levels of the series times 100.
The other expansion period density excludes the year before a new recession.
The p-value of the Kolmogorov-Smirnov test of the equality of densities is 0.000.

Figure 6:



Note: Lines show predicted probability given the indicated value of the x-axis variable, conditional on the other covariates. Bars show histogram of x-axis variable, with percent of sample shown on right axis. Underlying model is Table 3, column 9.

Figure 7:



Note: Lines show predicted probability given the indicated value of the x-axis variable, conditional on the other covariates. Bars show histogram of x-axis variable, with percent with percent of sample shown on right axis. Underlying model is Table 3, column 9.

Figure 8:

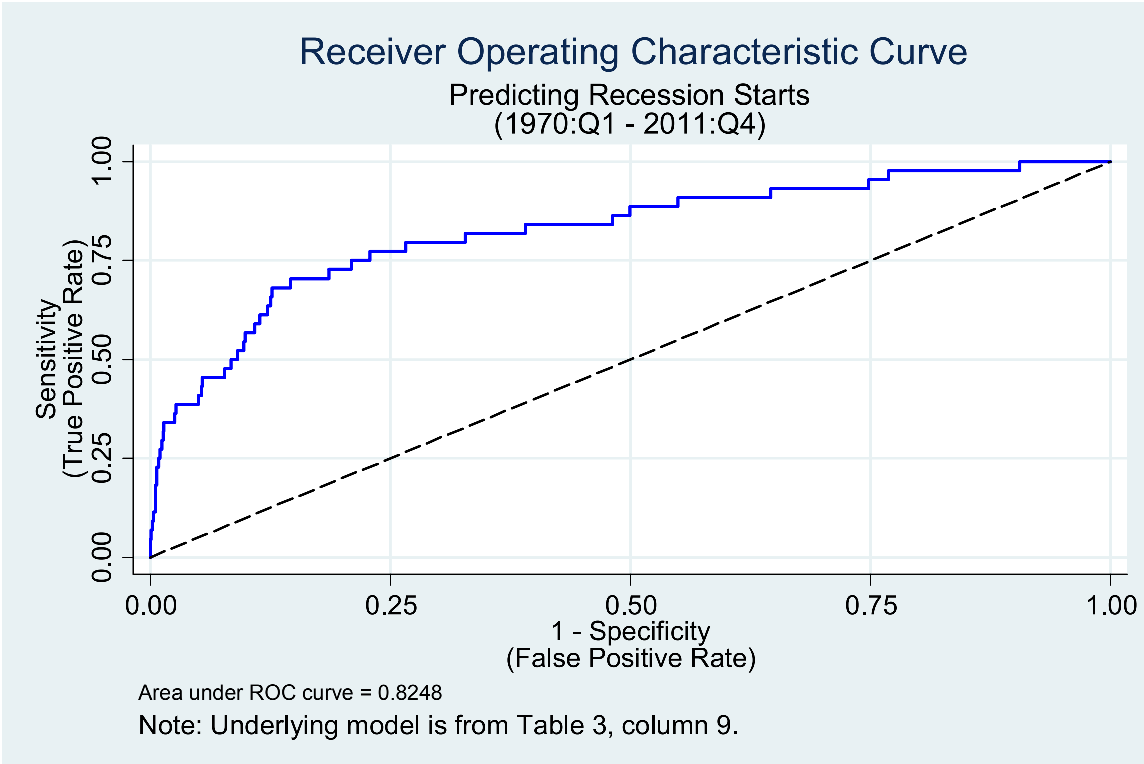
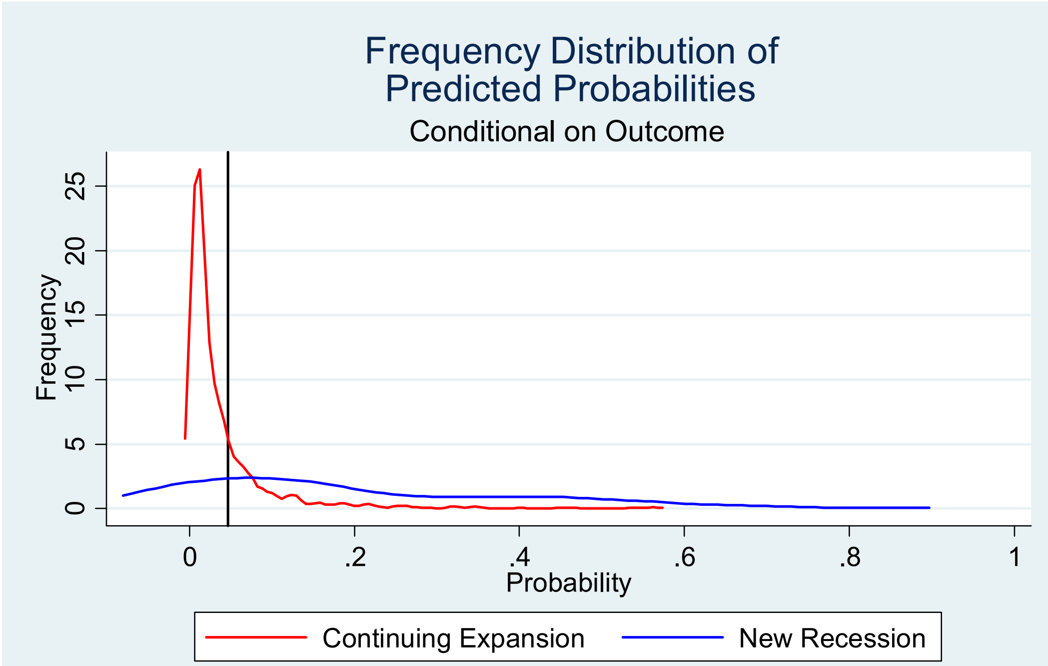
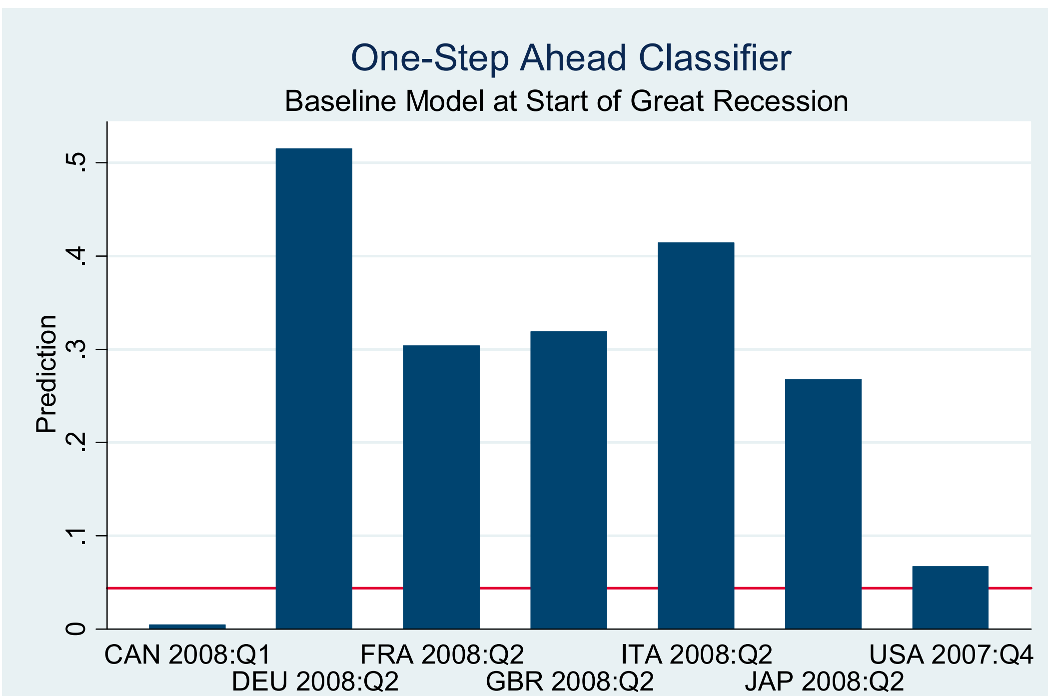

Receiver Operating Characteristic Curve
Predicting Recession Starts
(1970:Q1 - 2011:Q4)
Sensitivity
(True Positive Rate)
0.00
0.25
0.50
0.75
1.00
0.00
0.25
0.50
0.75
1.00
1 - Specificity
(False Positive Rate)
Area under ROC curve = 0.8248
Note: Underlying model is from Table 3, column 9.

Figure 9:



Note: These are the conditional densities of the predicted probabilities from the baseline model (Table 3, column 9). The unconditional probability of a new recession (vertical line) is 0.047. The p-value of the Kolmogorov-Smirnov test of the equality of densities is 0.000.

Figure 10:



Note: Underlying model is from Table 3, column 9. Red line indicates optimal classification threshold (Youden's J-statistic).