Technical Analysis and the Real Economy: Is there a Link?

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Abstract

This paper demonstrates that a significant link exists between the real economy and financial conditions proxied by technical indicators. We show that technical indicators distill the high frequency information of asset prices into useful signals of future economic activity. In-sample and out-of-sample results reveal that technical indicators forecast coincident indicators as well as the Conference Board's leading economic index and most of its components. Granger Causality tests support one-way causation from technical indicators to both coincident and leading economic indicators. Technical indicators further forecast financial stress, uncertainty, and recessions. Moreover, combining information from technical indicators and combination forecast methods lead to substantial gains in forecasting GDP including out-of-sample R^2 statistics of 28% over the last 30 years and 42% during recessions. We show that technical indicators 'work' because they jointly forecasts both economic conditions and stock returns.

Keywords:

JEL Classifications:

1. Introduction

For decades, technical analysis has been a frequently exploited tool of practitioners for forecasting the stock market (Schwager 1989, 1992, 2012; Billingsley and Chance, 1996; Covel 2005; Menkhoff and Taylor, 2007; Park and Irwin 2007; Lo and Hasanhodzic, 2009, 2010 and Han, Yang and Zhou, 2013). Academics however have been skeptical. They have raised concerns regarding technical analysis for two reasons. First, does it work? Can technical analysis survive rigorous econometric tests and forecast the stock market both in and out-of-sample?

Existing studies analyze the profitability of trading strategies based on a variety of technical indicators, including filter rules (Fama and Blume, 1966), moving averages (Brock, Lakonishok, and LeBaron, 1992), momentum (Conrad and Kaul, 1998; Ahn, Conrad, and Dittmar, 2003), and automated pattern recognition (Lo, Mamaysky, and Wang, 2000). Moskowitz, Ooi, and Pedersen (2012) further demonstrate that pervasive price trends occur across commonly traded equity indices as well as currency, commodity, and bond futures. Neely, Rapach, Tu and Zhou (2013) most recently find that technical analysis "display statistically and economically significant in-sample and out-of-sample forecasting power, matching or exceeding that of macroeconomic variables."

Second, more fundamentally, if technical analysis does work, why?[1] We address this concern as fellow academics remain cautious in embracing technical analysis since it seems counter to market efficiency. Technical indicators exploit past price and volume patterns to identify price trends expected to persist into the future. In contrast, the canonical random walk model, employed traditionally by academics and popularized to the public by Malkiel (1973, 2011), implies that future stock returns are unpredictable on the basis of currently available information. However, if economic fluctuations and aggregate risk are related and predictable, time-varying expected returns and return predictability can exist, even in an efficient market. And since asset prices are forward looking functions of the state variables of the real economy, asset prices may also exhibit significant business-cycle fluctuations, which maybe forecastable. Variables thus that predict the state of the economy hence should also predict returns (e.g., Fama and

[1] A popular economist's joke motivates this inquiry, "An economist is someone who finds something that works in practice and wonders whether it would work in theory." This paper provides an explanation for why it works in practice.

French, 1989; Campbell and Cochrane, 1999; Cochrane, 2007, 2011). This paper is the first to show that technical analysis 'works' because it jointly forecasts *both* the real economy and stock returns; further, combining the information from these joint forecasts lead to significant improvements in forecasting GDP.

There has been considerable work examining the influence of asset prices in forecasting economy (Fama, 1981; Harvey, 1989; Stock and Watson, 2003). Stock and Watson (2003) posit, "A simple model of stock price valuation is that prices equal the discounted expected value of future earnings; thus stock prices or returns should be useful in forecasting earnings or, more broadly, output growth." However, most work including Fama and Harvey and other work by Stock and Watson [1989, 1999] fail to find that stock returns provide accurate and consistent forecasts of GDP over-time. A key problem with the stock market's signal for future real economic activity is that the equity premia contains considerable contemporaneous high frequency news which may overwhelm information concerning future movements in jobs and GDP. In contrast, we show that technical analysis' moving average method extracts medium run trends from more noisy high frequency data and distills this noisy information into useful signals of future economic activity.

We adopt the most common technical analysis method of extracting medium to long run stock market movements by using a 12-month moving average of the stock return. In similar fashion, the most common predictors by academics of the stock market are the 12-month moving average of dividends or earnings divided by the stock price. Academics use the 12-month moving average for earnings and dividends for the same reason practitioners use the 12-month moving average of stock returns - to extract relevant signals from high frequency noise.

Stock market investors utilize moving average methods since many believe that the stock market fluctuates around its long-term mean, and employ technical analysis as a tool to guide them to finding this mean reversion. For example, John Bogle (2012), the legendary investor and founder of the prominent Vanguard Group, posits that the number rule of investing is "Remember reversion to the mean." Academic work including Poterba and Summers (1988), Balvers, Wu, and Gilliland (2000) has supported these mean-reverting tendencies, not on a day-to-day basis, but more likely to hold in the medium to long-run. Similarly, real economic activity has substantial business cycle swings, and many economists believe it is trend stationary (sometimes with infrequent breaks; e.g., Perron, 1989, Perron and Wada, 2009). This implies the economy mean-reverts around a long-run trend determined by technological progress. We assess whether technical analysis signal of mean reversion lead business cycles by estimating whether it can forecast recessions in real-time.

A second popular technical analysis method models stock prices asymmetrically, depending on whether stock prices are above or below their past 200 day average. The asymmetry in stock returns has been been cited by Ang and Chen (2002) and Cooper, Gutierrez, and Hameed (2004), while practitioners have long characterized stock price movements as up- and down-markets. Academics such as Hamilton (2005) and Owyang et al. (2013) have used Markov Switching methods to characterize the economy since they show the economy behaves differently depending on its state. Chauvet and Potter (2000) Markov model indicates that the stock market cycle leads the business cycle as expectations about changes in the future economic activity can have important predictive power to predict stock returns. If there are expectations about a coming recession, excess stock returns are low and after a recession period stock returns should be positive. Chauvet and Potter (2013) further have an insightful article using a dynamic factor Markov Switching models to forecast output, and show that forecasting ability depends on the business cycle.

This paper does not use these sophisticated Markov switching models that allow the economy to endogenously switch and behave differently in two states for several reasons. It is well known that complex models can be counter-productive in out-of-sample forecasting due to estimation errors, which is why the simple predictive regression model is the primary model used in the predictability literature. Our variable further is not only available in real time without revision, but also idetermined a priori exogenously relative to the dependent macroeconomic variable. Additionally, our definition is what many investors are actually using to assess the market state, and it is economically relevant to see how it works in practice. Instead of a two regime Markov switching model, our paper models the asymmetry by testing whether the technical indicator, constant and autoregressive parameters depend on the market's performance during the past 200 days. Second, we estimate a simple Markov switching model where the regimes depends exogenously on the past 200 day average to assess whether asset prices movements lead economic conditions.

A brief preview of our results reveals interesting findings. Technical indicators significantly improve forecasting both in-sample and out-of-sample relative to an autoregressive model for a wide range of monthly real economic variables including the Conference Board's four coincident indicators - employment growth, retail sales, industrial production, personal income and their diffusion index. Granger causality results demonstrate significant one-way causation from technical indicators to economic activity measured by these coincident indicators. Results further document that the adjustment to shocks of the dependent variables depends on whether the market is increasing or decreasing over the past 200 days. Moreover, a Markov-switching model where regimes depend on exogenous market conditions over the past 200 days is additionally supported by the data for all coincident indicators; the lagged technical indicators and autoregressive coefficients are distinctly different in the two regimes. Overall, results indicate very strong evidence that market conditions lead real economic activity.

Technical indicators further significantly forecast both in-sample and out-of-sample the Conference Board's LEI, its real and survey components (manufacturing new orders, nondefence orders, unemployment claims, hours, building permits, ISM, consumer confidence) and measures of financial stress (the St. Louis Stress index) and uncertainty (VIX, trading Volume and default ratios). Granger causality results also support one-way causation from technical indicators to these variables. Additionally, results support a Markov-switching model where past market conditions (over the past 200 days) determine the regimes for the LEI and its real components; the lagged technical indicators and autoregressive coefficients are distinctly different in the two regimes. Thus, results demonstrate very strong evidence that market conditions lead the leading indicators, which themselves lead real economic activity. Results also demonstrate that technical indicators are significant real time in-sample and out-of-sample predictors of recession one, two, three, six and twelve-months ahead; e.g., out-of-sample tests indicate 20% reductions in relative mean squared forecast error (MSFE) and 15% beyond the leading indicators. Technical indicators further supply additional information to the leading indicators index in forecasting recessions.

Using quarterly data, we also show that technical indicators significantly predict real GDP, investment, corporate profits, and dividends growth both in-sample and out-of-sample. Granger causality results again support one-way causation from technical indicators to these measures of real activity. The relationship to real profits and dividend growth is particularly salient; these measures are related to both broader economic activity such as real GDP and investment but also to the stock market.

Lastly, after demonstrating that technical indicators forecast a wide array of macroeconomic variables, we study in detail technical indicators ability to forecast GDP. We run a horse-race between GDP forecasts constructed using technical indicators against forecasts constructed using cluster methods (Aiolfi and Timmermann, 2006) and dynamic factor models.[2]. Results show that both technical indicator, cluster and dynamic factor forecast methods have R^2_{OS} statistics exceeding 11.6%, 18.4%, and 4.2% respectively. Most surprisingly, we construct a forecast of stock returns using technical indicators and use these *same* forecasts to predict GDP; the MSFE declines by 7.2%. Following Rapach and Strauss (2010), we then average the forecasts of the different methods. Averaging the forecasts constructed of the two technical indicator forecasts lead to R^2_{OS} of 18.9% and pooling the the dynamic factor model, cluster method and technical indicators leads to R^2_{OS} of 28.4%.[3]. Results further highlight that incorporating forecasts using technical indicators, cluster and dynamic factor methods leads to substantial gains during recessions and the past financial crisis (2007.1-2009.2); e.g., the R^2_{OS} statistic exceeds by more than 40% and 48%, respectively. Most interesting, the technical indicators forecasts of the stock market during recessions lead toR^2_{OS} of 5.7% for stock returns *and* 61.2% for GDP; that is, forecasts constructed using technical indicators of the stock market forecast GDP during downturns remarkably well. Overall, we provide the second missing piece to justify technical analysis widespread use in practice - technical analysis reflects the market expectations about the future evolvement of *both* the stock market and real economy, and the forecasts are particularly accurate in forecasting GDP during recessionary periods.

[2]Stock and Watson (2012) report that the dynamic factor model outperforms most Shrinkage models (including pretest models, Baynesian model averaging, empirical Bayes and bagging) in forecasting a wide array of macroeconomic variables including GDP

[3]As a comparison, Stock and Watson (2003, 2012) and Chauvet and Potter (2013) using simple combination methods and a dynamic Markov Switching model report MSFE declines in forecasting GDP of 5% and 12%, respectively

2. Data and Econometric Methodology

2.1. Data

The Conference Board publishes four monthly coincident indicators and a diffusion index; these variables represent current economic activity. Monthly data covers 1960.1-2013.04. These are:

EMP Employees on nonagricultural payrolls (thous.)
IP Index of industrial production (2007=100)
PI Personal income less transfer payments (AR, Chain 2005 $)
SAL Manufacturing and retail sales (AR, Chain 2005 $)
DIF Diffusion index of coincident indicators, 1-mo. span (pct.)

Additionally, we consider a fifth coincident indicator from the Conference Board - capacity utilization. This variables is a popular economic measure of current economic activity, and used by the Federal Reserve as an indicator of the business cycle and inflationary pressure.

CU Capacity Utilization rate total industry (pct.)

Unit root tests (Elliot, Rothenberg and Stock Point optimal tests) indicate the four coincident variables contain a permanent component; hence, we log difference them to create growth rates. The capacity utilization rate is also highly persistent and we difference this variable. The Conference Board additionally publishes ten leading indicators and an index:

HRS Average weekly hours, mfg. (hours)
CLA Average weekly initial claims, unemploy. insurance (thous.)
ORD Mfrs' new orders, consumer goods and materials (mil. 1982 $)
ISM new orders, diffusion index (pct.)
$ORDN$ Mfrs' new orders, nondefense capital goods excl. aircraft (mil. chain 1982 $)
BP Building permits for new private housing units (thous.)
SP Index of stock prices, 500 common stocks, NSA
$M2$ Money supply, M2 (bil. chain 2005 $) (LEI comp. until Apr 1990)
YD Interest rate spread, 10-year Treasury bonds less federal funds
$CEXP$ Consumer expectations, NSA
LEI - Composite index of 10 leading indicators (2004=100)

HRS, CLA, ORD, ORDN, BP, M2, YD and LEI are nonstationary; we log difference CLA, ORD, ORDN, BP and M2 and difference HRS and YD to induce stationarity. Following Huang and Zhou (2013), we use a Hodrick Prescott filter to induce stationarity.

To measure economic uncertainty and economic turbulence as well as the business cycle, we also consider the following monthly variables:

DFR The AAA-BAA bond obtained from Goyal and Welch
VOL Stock market volume measured by the NYSE obtained from Global Financial Data
STR Financial Stress index produced by the St. Louis Federal Reserve. 1975.1-2013.04
REC NBER recession dates, where a 1 indicates a recession.

Quarterly data are from FRED (St. Louis Federal Reserve) and cover 1960.1-2013.1:
$RGDP$ Real Gross Domestic Product
DIV Real Dividend payments
PRO Real Profits
$PROA$ Real Nonfinancial Corporate Business: Profits After Tax
$INVT$ Real Gross Private Domestic Investment
$PFNI$ Real Private Nonresidential Fixed Investment
All quarterly variables are logged differenced to create growth rates, and the DFR variable described above is also differenced.

2.2. Econometric Methodology

Following Huang and Zhou (2013), we use two measures of technical indicators. The first measure is a twelve-month moving average defined as:

$$TECH_t = \frac{r_{t-12\to t} - \mu}{\sigma_{t-12\to t}} \tag{1}$$

where $r_{t-12\to t}$ is the cumulative return of the S&P 500 index over the year from month $t-12$ to month t, μ is its long-term mean constructed as recursive average beginning in 1950 , and $\sigma_{t-12\to t}$ is the annualized moving average standard deviation estimator (Officer, 1973; Mele, 2007).

A second method constructs an indicator up-down variable based on whether the current stock price is above or below its last 200 days moving average. In practice, the 200-day moving average has been widely plotted and exercised for years in investment letters, trading softwares, and newspapers (such as Investor Business Daily). Note, this indicator may have self-fulfilling properties; for instance, if enough investors believe it, they may herd on this information, thereby generating impact on the market price (see, e.g., Froot, Schaferstein, and Stein, 1992; Bikhchandani, Hirshleifer and Welch, 1992), and making it necessary to study the predictability across the up- and down-markets.

$$I_{up,t} = \begin{cases} 1, & \text{if } P_t \geq \frac{1}{200}\sum_{i=1}^{200} P_{t+1-i} \text{ ;} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The technical variable may interact with the indicator variable if the stock market behaves differently whether it is rising or declining, $TECH_t * I_{up,t}$. This asymmetric behavior occurs if investor behavior differ in up or down markets. For example, in up markets, since investors have abundant capital due to rising prices and less constraints on borrowing, they may buy aggressively when TECH is negative, which drives the price up and lifts the future return back to its long-term mean or above it. For the sign in the down-markets, there are two intuitive reasons. First, as many investors follow the down-market indicator, they may not buy aggressively in a down-market or even start selling to reduce stock exposure. Second, those investors who use leverage are likely forced to sell as margins relative to asset values

We model economic activity as an AR process and technical indicators:

$$ECON_t = \alpha + \beta_1 TECH_{t-1} + \beta_2 TECH_{t-1} I_{up,t-1} + \sum_{j=0}^{q_1} \gamma_j ECON_{t-j} \tag{3}$$

If increases in past stock market returns forecast increases in current economic activity, $\beta_1 > 0$; further, if this effect is market dependent and negative in down markets, $\beta_2 < 0$. Additionally, we also estimate

$$ECON_t = \alpha + \beta_1 TECH_{t-1} + \beta_2 TECH_{t-1} I_{up,t-1} + \beta_3 I_{up,t-1} + \sum_{j=1}^{q_1} \delta_j I_{up,t-j} ECON_{t-j} + \sum_{j=1}^{q_1} \gamma_j ECON_{t-j} \tag{4}$$

This equation allows for different constant and different lagged adjustment depending on stock market conditions; all variables in this equation are allowed to behave differently depending on the state. We differentiate this equation from equation (2) for two reasons. First, we are interesting in assessing whether stock market conditions affect the lagged adjustment of economic variables; second, we will perform out-of-sample tests and wish to keep the model relatively simple. Equations that are highly parameterized tend to perform relatively poorly out-of-sample; hence, our out-of-sample tests will compare (3) to an autoregressive model.

3. Results

Before we present in-sample, out-of-sample, Granger Causality and Markov Switching results, Tables 1-2 present simple summary cross autocorrelation patterns of real economic activity with our two technical indicators ($TECH, TECH * I_{up}$), stock returns (SR) and the leading economic index (LEI). The magnitude and significance of lagged TECH's correlation to current real economic activity, particularly compared to lagged SR and LEI indicators, will preview the striking results we subsequently present using more sophisticated econometric tools. Table I presents the correlation between $TECH_t, TECH_{t-1}, TECH_{t-3}$, and $TECH_{t-6}$ and the five coincident indicator correlation patterns. We also report the relationships of $LEI_t, LEI_{t-1}, LEI_{t-3}, LEI_{t-6}$ and $SR_t, SR_{t-1}, SR_{t-3}, SR_{t-6}$ with economic activity at time t to assess whether these variables lead economic activity more than technical indicators. A variable leads economic activity if its cross autocorrelation patterns peaks before real activity.

Results clearly show that $TECH$ is not only positively contemporaneously correlated with all coincident indicators, but also $TECH_{t-1}, TECH_{t-3}, TECH_{t-6}$ are significantly positively correlated; e.g., the t statistics printed below the correlation coefficients for $TECH_{t-1}$ and $TECH_{t-3}$ exceed five, and for $TECH_{t-6}$ exceed five for all variables except personal income. Thus, increases in the moving average indicator are strongly related to increases in future economic activity. Correlation patterns with real economic activity tend to peak for $TECH_{t-3}$, indicating that $TECH$ leads rises in real economic activity by one quarter.

Although TECH is extracted from lagged stock returns, the correlation magnitude of lagged stock current with economic activity is substantially less than TECH. More striking, although the LEI and its lags are significant predictors of real economic activity, the lagged LEI coefficients estimates and t statistics are always smaller and less significant than corresponding lagged TECH. Note, the absolute value of the estimates (since the recession coefficient is always negative) for $TECH_{t-1}$ and $TECH_{t-3}$ is .34 and .36, while for SR_{t-1} (LEI_{t-1}) and SR_{t-3} (LEI_{t-3}) it is .08 (.16) and .18 (.11); the correlations are half the TECH estimates. Note, LEI correlation pattern for most variables peaks contemporaneously or at $t-1$, while SR peaks at $t-3$ and $t-6$ its signal (estimates) are considerably weaker. Thus, lagged TECH is substantially more correlated with future economic activity than stock returns or the leading economic indicator.

The last column of the table clearly shows that lagged TECH is also a significant predictor of Recessions; e.g., $TECH_{t-1}, TECH_{t-3}$ and $TECH_{t-6}$ estimates are -.55, -.48 and -.36 with t statistics all exceeding five. SR_{t-1}, SR_{t-3}, and SR_{t-6} are -.22, -.25 and -.24 and LEI_{t-1}, LEI_{t-3} and LEI_{t-6} is -.25, -.15, -.02 and again less than half the $TECH$ estimates. Note further, $TECH * I_{up,t-1}, TECH * I_{up,t-3}$, and $TECH * I_{up,t-6}$ are also significant in cases but one with real economic activity, although the magnitudes of their relationships is smaller than $TECH$.

Table 2 presents the cross correlation patterns for quarterly variables. Contemporaneous real GDP correlation coefficients (t stats) with $TECH_{t-1}$ and $TECH_{t-2}$ are .35 (5.4), .31 (4.8); substantially stronger than LEI_{t-1}, LEI_{t-2} correlation coefficients of -.18 (2.7) and -.19 (2.7). The stock return is significant as SR_{t-1}, SR_{t-2} of .25 (3.7) and 3.1 (4.6). $TECH_{t-1}$ and $TECH_{t-2}$ is a significant predictor of real dividends, profits, after-tax profits, investment and Private nonresidential investment. In all cases, the correlations coefficients are larger than the LEI. These preliminary statistics highlight that TECH is strongly correlated with future economic activity, business cycles (recessions) and business performance (measured by dividends and profits).

Table 3 presents in-sample regressions for the Conference Board's four coincident indicators, their diffusion index and capacity utilization. We report the coefficient estimates and t statistics (using Newey-West adjusted standard errors) for the two technical indicators $\beta_{1,t}$; the lagged AR coefficients and constant are not reported for conciseness. We use AIC criteria to choose AR lag lengths, and they typically range from three to four. TECH is positively significant at the 1% for all five variables with t statistics in all cases exceeding three; additionally, $TECH * I_{up}$ is significant at least at the 5% for all five coincident indicators. The χ^2 jointly tests both technical indicators and exceed twenty with a Prob. of .0001; hence, there is very strong statistical evidence that technical indicators forecast employment, industrial production , retail sales, and income growth. χ^2 in row 10 rejects symmetric adjustment of the lag AR coefficients, and supports economic adjustment depends on market conditions.

The bottom half of Table 3 presents bivariate Granger Causality results. The F statistics and accompanying P values demonstrate strong one-way causation from TECH to all five coincident indicators; e.g., F statistics reject with Prob. of 0.001 that TECH does not Granger Cause coincident economic activity *and* results can not reject the null hypothesis that coincident economic activity does not Granger Cause TECH.

For comparison (to differentiate from $TECH * I_{up}$) and because the 200-day moving average variable is a widely reported stock market indicator, we report Granger Causality results between the UP/DOWN Indicator variable in equation (2) and coincident variables. There is also strong evidence that the 200-day moving average indicator significantly leads economic activity by several months.

Hamilton (2005) argues persuasively that the economy should be modelled by a Markov Switching model since it behaves differently depending on the regime. We use a simple Markov Switching framework, where the I_{up} indicator exogenously determines the switching regimes. Results in Appendix I clearly show very distinctive regimes; for instance, for employment growth (column I), the $TECH_{t-1}$ parameters for regime 1 (2) are .2 (.06) and .03 (.03) and the EG_{t-1} and EG_{t-2} are -.35 (.10) and .95 (.11) for regime 1 and .41 (.05) and .18 (.04) for regime 2. The last two rows report in Column one show that the probability parameter and Z statistics for different regimes are -1.9 with a Z statistic nearly -4; this is significant with Prob. 0.001 that the regimes are identical. Additionally, inspection of both $TECH_{t-1}$ and/or AR parameters for industrial production growth, personal income growth, the diffusion index and change in capacity utilization (columns II-V) indicate substantially different regimes determined by the 200 day stock market indicator. The last column presents that the leading economic indicator also exhibits distinct Markov Switching behavior.[4]. The results further support clear evidence of different regimes depending on past market conditions identified by the 200-day technical indicator.

Table 4 reports out-of-sample results for one, three and six month horizons of the technical indicators and the simple combination of their forecasts. The simple combi-

[4]For conciseness, we do not report the Markov Switching results for the leading indicator components; however, results are similar for the real economic and survey components that we present regression results for in Tables V-VI

nation averages the forecasts of both technical indicators.[5]. The Clark West statistics, which are adjusted to yield normal critical values, exceed 2.3 in all six cases at the one-month horizon, and their Probability (P) values are presented below indicate all variables ance are significant at approximately the 1% significant level for TECH. The $TECH*I_{up}$ is not significant out-of-sample; simple combinations of both these estimates are significant at the 5% level for all six variables. At the three and six month horizons, the TECH variable has Clark West statistics exceeding 3.0, and hence is very significant. The $I_{up,t-1}$ is significant for five of six variables (except retail sales), and all six variables at the six month horizon. A simple combination of both technical indicators is significant at the 1% for all six variables. Thus, there is strong evidence that technical indicators provide significant real-time predictors of coincident economic activity.

Tables 5-6 present the leading indicator components that measure real activity including manufacturing new orders, nondefence orders, unemployment claims, hours, building permits, ISM, and consumer confidence. VII and VIII present the financial leading indicators (stock return, yield curve and money growth) as well as three other financial variables. Results in Table V show that TECH is a significant predictor of all seven real and survey variables. These variables are leading indicators because historically they have been shown to lead economic activity. T statistics exceed 3.0 for all seven components, and hence are significant with Prob. 0.001. The I_{up} variables are significant at the 5% for new orders, building permits, consumer expenditures and ISM. The χ^2 statistic that jointly tests both technical indicators is significant at 1% for all seven variables. χ^2 statistics for lagged adjustment is significant for new orders, nondefence orders and consumer expectations. Granger causality results significantly reject no causation for TECH at the 1% level (F statistics all exceed 7, and thus are very significant). Moreover, Granger results for I_{up} also support one-way causation as the F statistics exceed 6.0 and thus are also highly significant, while F statistics from leading indicators to $I_{up,t-1}$ are not significant. Thus, results very strongly support one-way Granger Causality from technical variables to leading indicators. Up and Down market conditions further substantially explain the leading indicator. Distinct evidence of regime dependent market conditions is also valid for the leading indicator components

[5]We also investigated out-of-sample results results using forecasts of equation (3); the bivariate equation results were relatively similar to the combination forecasts and did not change inference for most equations

in Table 4-5, and most financial variables and quarterly data including investment and dividend growth in Tables 6-10.[6]

Results in Table 6 clearly indicate significant out-of-sample predictability. TECH is significant at the one-month horizon for all seven variables; however, the I_{up} indicator variable does not lead to significantly lower MSFE out-of-sample. The combination of the technical indicators is significant for six of the seven variables. At the three and six month horizon, TECH and the combination predictor are also significant for six of the seven variables. Overall, the evidence demonstrates that technical variables lead leading indicators; hence, they represent forward looking indicators of economic activity. The χ^2 statistic exceeds 10.0 and is significant at 1%. However, technical variables do not lead the yield curve and real money growth. The χ^2 statistic for both variables is less than 5.0. We also examine the Default rate, Volume and Financial Stress. The Default rate and volume are measures of economic uncertainty or confidence, and has been used as an equity predictors.

Table 7-8 present the three financial leading indicators, the leading indicator index as well as four other prominent financial measures. Column I shows that technical indicators are a significant predictor of stock returns and is consistent with Huang and Zhou (2013); TECH (TECHI_{up}) is significant at the 5% (1%) level and both indicators are jointly significant at 1% significant[7] The technical variables are not significant predictors of the last two leading indicators, the yield curve and money growth; further, there is no significant Granger Causality in either direction. Technical indicators however significantly forecast other relevant variables that are predictors of stock returns - these include the default rate, volume and net stock issuance; e.g., the χ^2 statistic are significant at the 1% level for all three variables. Additionally, there is significant evidence that TECH one-way Granger Causes all three financial predictors. Both technical indicators are significant predictors of financial stress as the t statistics exceed two, and their joint χ^2 test is also significant at the 5% level. Results for the Kansas City stress index are qualitatively similar. Additionally, there is very strong evidence that TECH and I_{up}

[6]The coefficient estimates (t statistics for instance of real dividend growth are .20 (7.3) and .02 (4.0) and hence are significant and substantially different in the regimes; these results are available upon request.

[7]Note, the Granger Causality results here show that stock returns Granger Cause the technical indicators; however, this is by construction. The technical indicators are moving average/backward representations of stock returns.

one-way Granger Cause Financial Stress. Since the Financial Stress indicators index are a composite of financial variables that represent forward looking measures of economic activity, technical indicators also predict financial stress and economic activity. Lastly, Column VIII shows that both technical indicators are very significant predictors of the leading indicator index. Given that the LEI is a composite of ten leading indicators of the economy, it must also be true that technical indicators significantly lead economic activity. Granger Causality results further demonstrate very significant one-way causation from TECH to LEI and from the 200-day I_{up} indicator to LEI. Out-of-sample forecasts in Table 8 support the in-sample results; technical variables predict the stock return, default rate, volume, net stock issuance, financial stress and leading indicators at multiple horizons (1, 3, and 6). Overall, the results exhibit very strong evidence that technical indicators lead financial variables and economic activity.

Tables 9 and 10 demonstrate that technical variables are significant predictors of relevant quarterly variables including growth in real GDP, investment, private nonfinancial investment, profits, after-tax profits and dividends.Dividends also are available monthly; results are similar; e.g., the t stat for TECH is 3.83). Column I shows that both technical variables significantly forecast real GDP growth; moreover, one-way Granger Causality results occurs from TECH and TECHI_{up} to real GDP. Technical variables also forecast real growth in investment, private nonresidential investment, profits, after-tax profits and dividends. Granger Causality results further support one-way causation from both TECH and TECH*I_{up} to growth in real economic activity, business profits and dividend distribution. Out-of-sample results support predictability for all six variables at the 1-month horizon, and for TECH at 3-month horizons for GDP, investment, private nonfinancial investment, after-tax profits and dividends at 5%. The last column is particulary salient; TECH significantly forecasts real dividend growth in-sample and out-of-sample at 1, 3 and 6 month horizons; further Granger Causality results show one-way causation from technical indicators to higher dividend growth.

Tables 11 demonstrates that technical indicators forecast recessions in-sample and out-of-sample. Since recessions on average are declared by the NBER ten months after they begin, they are not known in real time; hence, we do not use lagged recession data and do not present Granger Causality results. Allowing for lagged recession results however does not qualitatively change the results; e.g. TECH is significant in column

(1) at the 1% level and the χ^2 exceeds 8 (10) for Granger Causality from TECH (I_{up}) to Recession and less than 2 (2) from Recess to TECH (I_{up}). This supports very significant one-way Granger Causality from technical indicators to recession. Table X forecasts recessions at the 1, 2,3 and 6 month horizons in-sample and presents three models:

$$Recess_t = \alpha + \beta_1 TECH_{t-1} + \beta_2 TECH_{t-1} I_{up,t-1} \tag{5}$$

$$Recess_t = \alpha + \beta_1 TECH_{t-1} + \beta_2 TECH_{t-1} I_{up,t-1} + \beta_3 LEI_{t-1} \tag{6}$$

$$Recess_t = \alpha + \beta_3 LEI_{,t-1} \tag{7}$$

Recessions are estimated using a binary, probit model (as they are 1 or 0 variables) and robust standard errors are reported. Estimates in column I for lagged TECH are very significant with t statistics exceeding 10. The R^2 are above 35%, implying that technical indicators forecast a considerable portion of the variance of recessions. Results for equation (6) show that the LEI is a significant predictor of recessions, but adds only marginal explanatory power as the R^2 increases modestly. Further, equation (7) indicates that LEI's explanatory power in forecasting recessions is substantially less than technical indicators. Inspections of β_1 and β_1 between equations (6) and (7) indicate that LEI does not influence the estimates. Out-of-sample results in the bottom half of the table indicate that technical indicators can forecast recessions in real time. Results in columns II-V show that technical variables also predict recessions 2,3 and 6 horizons ahead relatively accurately; e.g., $TECH_t$ and $TECH * I_{up,t-1}$ are very significant predictors of recessions over the next six months and can explain nearly 50% of the variance, while the LEI_{t-1} can only explain less than 3% of the variance. Out-of-sample for recessions over the next six months further show that both $TECH_t$ and $TECH_t I_t$ and their combination are very significant predictors of recessions in real time.

Additionally, we show when analysts are conducting technical analysis of the stock market, they are implicitly forecasting the real economy - and vice versa. To demonstrate this, we first take technical analysis' forecasts of the stock market, and use them to forecast economic variables. For simplicity, the economic variables are the business cycle (recessions),uncertainty (financial stress, VIX) and job growth.

$$\hat{S}R_t = \alpha + \beta_1 TECH_{t-1} + \beta_2 TECH_{t-1} * I_{up,t-1} \tag{8}$$

$$\hat{E}CON_t = \gamma 1 \hat{S}R_{t-1} \tag{9}$$

The γ_1 coefficient ($tstat$) for recession, financial Stress, volatility (VIX) and job growth are -.91 (8.7), -.75 (7.4), -5.3 (2.6) and .08 (5.4) with adjusted R^2 of 16%, 19%, 11% and 4%, respectively. Hence, forecasts for the stock return significantly predict economic activity. Second, we take the forecasts from economic activity and combine them to forecast stock returns.

$$\hat{E}CON_t = \alpha + \beta_1 TECH_{t-1} + \beta_2 TECH_{t-1} * I_{up,t-1} \tag{10}$$

$$\hat{S}R_t = \alpha + \gamma 2 \hat{E}CON_{t-1} \tag{11}$$

The in-sample γ_2 estimate is -.07 (2.6); and the out-of-sample R^2 is 1.54%. This is significant at the .1% level and indicates meaningful stock market predictability. Thus, technical analysis jointly forecasts both economic activity and the stock market.

Can we use this method to help forecast GDP? And how do technical indicators compare to other methodologies in forecasting GDP? We use two combination forecast methods. First, we use a simple combination method that averages the bivariate ARDL models. Stock and Watson (2004) find that simple combination forecast outperform more complicated methods for forecasting GDP across the G7 economies; Smith and Wallis (2009) present a formal explanation of the 'simple combination puzzle', which posits that simple combination are repeatedly found to outperform more complicated weighted combinations in empirical applications. Genre, Kenny, Meyler and Timmermann (2012) show that simple combination forecast of expert surveys of European GDP outperform most combination strategies. Second, we use Aiolfi and Timmermann (2006) cluster method that groups the ARDL models into different clusters depending on their forecasting ability; it then pools the forecasts of the cluster that performs well in past periods according to combination weights that are partially shrunk toward equal weights. They show that trimming the worst performing models helps forecast output growth in most of the G7 economies. Additionally, we also combine information using a dynamic factor model (this differs from combining forecasts as the factors are extracted from the macroeconomic data, not the forecasts). Recently, Stock and Watson (2012) show that dynamic factor models outperform nearly all shrinkage models in forecasting a wide array of macroeconomic variables including GDP. Our combination methods use 84 quarterly variables (which are presented in Appendix II), the dynamic factor model uses 3 factors (4 or 5 factors lead to lower performance) and the cluster method also uses three clusters.

Table 12 reports the forecasts for GDP for different time periods and one and two quarter horizons. The full-sample period covers 1982.1-2013.2, and sub-samples are 1992.1-2011.1[8], 2000.1-2013.2, 2007.1-2013.12 (a period of substantial economic turbulence), 2007.4-2009.2 (the financial crisis recession), recessions and expansions. The recession and expansions use NBER quarterly cycle dates, and cover the 1982, 1990, 2001 and 2007-2009 recessions. We report the R^2_{OS} which is constructed as 1 - MSFE ratio (relative to the AR benchmark). Clark-West statistics of the $MSFE - adjusted$ statistic determine significance.

Column I presents the technical forecasts using equation (3), while Column (2) uses equations (8) and (9) to assess whether forecasts constructed using technical indicators of the stock market also jointly forecast GDP. Column (3) averages the two forecasts and leads to substantial and significant forecasting gains of 18.9% for the full sample and 16.8% from 1992.1-2011.1, and hence out-performs the dynamic Markov Switching model. Technical indicators hence extract relevant information from the stock market that are relevant to future economic activity, and we can these indicators to construct forecasts of the stock market that help forecast GDP; e.g., Harvey, Leybourne and Newbold (HLN, 1998) forecast encompassing tests of equations (3) and (9) reject no encompassing at the 1% level. Rejecting the null of 'no encompassing' implies that *both* forecasts possess significant useful information in forecasting GDP, and that combining information from the different forecasts can lead to increase in forecasting gains and a rise in the R^2_{OS}. Results for the recent time period, 2000 and 2007, also exhibit large R^2_{OS} statistics (approximately 20% and 40%, respectively), and combining information from technical forecasts of GDP and stock market lead to significant increases in R^2_{OS} of GDP.

How do other forecasting procedures perform? The simple combination, dynamic factor model and cluster methods lead to R^2_{OS} for the full sample of 13.2%, 4.2% and 16.6%, respectively. Larger R^2_{OS} statistics of 24.6% and 22.3% occur if we average the two technical indicators (the foreca sts in columns (1)and (20)) with cluster or simple

[8]This period coincides with the work of Chauvet and Potter (2013) who using a dynamic factor Markov Switching model find gains of 10.7% and 8.9% for forecasting GDP at the one and two quarter horizons, respectively

combinations. Lastly, if we pool the forecasts of these technical indicators, clusters (or simple combination) with diffusion we obtain R^2_{OS} of 28.4% (27.3%). Results for forecasting GDP at the two-quarter horizon are roughly similar, the four forecasting pooled methods both lead to R^2_{OS} of approximately 28%. The R^2_{OS} are more double Chauvet and Potter's findings, and considerably more than Stock and Watson 4% R^2_{OS} for 1982.1-1998.4; e.g., during this period, the four combination approach both lead to R^2_{OS} exceeding 28%.[9] Technical indicators hence possess information to forecasting GDP, and the results are robust across different time periods.

How do these approaches work during recessions? The four pooled combination forecast methods lead to R^2_{OS} between approximately 40-42%, and also forecast remarkably well during the financial crisis, with R^2_{OS} exceeding 45%. Most surprisingly, the best forecasting model of GDP during both the financial crisis and recessions by a considerable margin is the forecasts constructed of the stock market using technical indicators (equations (8)-(9)), as the R^2_{OS} exceeds 61% during recessions and 75% during the financial crisis. Results for the two-quarter horizon reveal R^2_{OS} of 61% during recessions and 59% during the financial crisis. Technical indicators are used typically to forecast the stock market; however, they represent far more accurate measures of GDP during recessionary periods; e.g., technical indicators using equation (8) forecast the stock market during the full sample 3%, which rises to 5.7% during recessions. The significance of equation (8) in forecasting *both* stock returns and GDP, imply that technical indicators 'work' through their relatively accurate forecasts of GDP. Therefore, there is a very strong link between technical indicators and further macroeconomic activity.

4. Conclusion

NOT DONE YET.

[9] Forecasting gains occur because the forecasts contain different information; e.g., HLN forecast encompassing tests reject no encompassing at the 1% level for all four combinations presented in Columns (7)-(10), hence pooling information from the different forecasts can lead to forecasting gains.

Table 1: **Monthly Data Cross Autocorrelations**

VAR	EG_t	IPG_t	PIG_t	$SALEG_t$	$\triangle CU_t$	DIF_t	REC_t
$TECH_t$	0.295	0.319	0.230	0.231	0.305	0.388	-0.541
	7.255	7.914	5.551	5.575	7.528	9.876	-9.732
$TECH_{t-1}$	0.332	0.346	0.230	0.212	0.328	0.380	-0.546
	8.274	8.644	5.554	5.098	8.148	9.650	-9.853
$TECH_{t-3}$	0.394	0.377	0.284	0.211	0.355	0.428	-0.483
	10.057	9.552	6.949	5.071	8.915	11.130	-8.341
$TECH_{t-6}$	0.351	0.272	0.238	0.147	0.243	0.384	-0.358
	8.805	6.633	5.743	3.478	5.876	9.770	-5.800
$TECH_t I_{up,t}$	0.141	0.178	0.128	0.129	0.169	0.218	-0.205
	3.332	4.235	3.020	3.047	4.037	5.234	-3.176
$TECH_{t-1} I_{up,t-1}$	0.160	0.187	0.110	0.096	0.178	0.168	-0.186
	3.807	4.476	2.602	2.254	4.244	4.009	-2.870
$TECH_{t-3} I_{up,t-3}$	0.171	0.148	0.150	0.069	0.136	0.174	-0.175
	4.072	3.520	3.558	1.631	3.226	4.157	-2.687
$TECH_{t-6} I_{up,t-6}$	0.122	0.128	0.125	0.087	0.109	0.177	-0.148
	2.879	3.025	2.952	2.045	2.563	4.222	-2.258
SR_t	0.010	-0.012	0.082	0.113	-0.011	0.081	-0.160
	0.245	-0.287	1.939	2.662	-0.256	1.905	-2.458
SR_{t-1}	0.034	0.037	0.043	0.112	0.034	0.080	-0.220
	0.804	0.881	1.000	2.646	0.792	1.881	-3.409
SR_{t-3}	0.129	0.236	0.110	0.143	0.225	0.159	-0.249
	3.058	5.699	2.594	3.391	5.411	3.787	-3.884
SR_{t-6}	0.132	0.166	0.111	0.132	0.156	0.204	-0.242
	3.121	3.942	2.625	3.119	3.710	4.892	-3.768
LEI_t	0.310	0.148	0.200	0.085	0.060	0.262	-0.289
	7.657	3.505	4.800	1.998	1.410	6.367	-4.563
LEI_{t-1}	0.279	0.108	0.177	0.046	0.020	0.221	-0.289
	6.811	2.543	4.216	1.069	0.475	5.314	-4.563
LEI_{t-3}	0.212	0.038	0.132	0.008	-0.047	0.156	-0.244
	5.085	0.900	3.121	0.190	-1.103	3.705	-3.812
LEI_{t-6}	0.102	-0.046	0.061	-0.043	-0.126	0.055	-0.141
	2.414	-1.084	1.433	-1.015	-2.991	1.287	-2.149

Table 1 presents correlations and cross correlations of the coincident indicators with $TECH$, $TECH * I_{up}$, stock returns (SR) and the leading economic indicator (LEI). Correlation coefficients and standard errors are presented. $EG, IPG, PIG, SALEG$, $\triangle CU, DIF$, and REC are employment growth, industrial production growth, real personal income growth, real sales growth, differenced capacity utilization, diffusion index and recession, respectively.

Table 2: **Monthly Data Cross Autocorrelations**

VAR	GDP_t	DIV_t	PRO_t	$PROA_t$	$INVT_t$	$PFNI_t$
$TECH_t$	0.306	0.326	0.172	0.182	0.319	0.177
	4.651	4.993	2.527	2.671	4.872	2.599
$TECH_{t-1}$	0.350	0.345	0.172	0.233	0.373	0.363
	5.410	5.319	2.518	3.471	5.819	5.630
$TECH_{t-2}$	0.315	0.277	0.118	0.164	0.394	0.444
	4.793	4.166	1.722	2.401	6.206	7.161
$TECH_t I_{up,t}$	0.132	0.257	0.084	0.086	0.238	0.061
	1.925	3.837	1.213	1.243	3.542	0.887
$TECH_{t-1} I_{up,t-1}$	0.132	0.191	0.052	0.070	0.188	0.171
	1.925	2.807	0.752	1.008	2.767	2.513
$TECH_{t-2} I_{up,t-2}$	0.128	0.143	0.019	0.062	0.163	0.189
	1.862	2.091	0.268	0.905	2.385	2.784
LEI_t	-0.175	0.033	0.048	0.037	-0.058	-0.102
	-2.572	0.484	0.691	0.537	-0.835	-1.482
LEI_{t-1}	-0.181	0.029	0.045	0.034	-0.062	-0.106
	-2.658	0.420	0.653	0.495	-0.904	-1.540
LEI_{t-2}	-0.187	0.024	0.043	0.031	-0.067	-0.111
	-2.749	0.351	0.616	0.454	-0.973	-1.610
SR_t	0.082	0.029	-0.084	0.072	-0.034	0.178
	1.183	0.417	-1.202	1.027	-0.486	2.589
SR_{t-1}	0.250	0.096	0.252	0.258	0.120	0.161
	3.729	1.392	3.770	3.861	1.752	2.356
SR_{t-2}	0.308	0.112	0.116	0.133	0.387	0.305
	4.687	1.637	1.687	1.934	6.072	4.624

Table 2 presents correlations and cross autocorrelations of the relevant real quarterly data with $TECH$, $TECH * I$, stock returns and the leading indicator. Correlation coefficients and standard errors are presented. $GDP, DIV, PRO, PROA, INVT and PFNI$ are real gdp, dividend, profits, after-tax profits, investment and private nonresidential fixed investment growth, respectively. All variables are real.

Table 3: **In-Sample and Granger Causality Tests for Coincident Indicators**

VAR	EG_t	IPG_t	PIG_t	$SALEG_t$	DIF_t	$\triangle\ CU_t$
$TECH_{t-1}$	0.171	0.729	0.438	0.974	29.522	2.008
	4.313	5.224	3.402	5.007	5.138	4.645
$TECH_{t-1} * I_{up,t-1}$	-0.147	-0.519	-0.352	-0.695	-28.286	-1.511
	-2.789	-2.626	-2.32	-2.391	-3.79	-2.379
χ^2	21.03	35.77	21.03	35.77	27.68	21.03
	0.001	0.001	0.001	0.001	0	0.001
R^2	0.505	0.209	0.505	0.209	0.309	0.061
	0.48	0.171	0.48	0.171	0.275	0.021
R^2	0.517	0.224	0.517	0.224	32.23	0.086
χ^2	14.48	10.51	14.48	10.51	19.71	13.69
	0.001	0.03	0.001	0.03	0.001	0.008
$TECH_{t-i} \nRightarrow ECON_t$	8.756	10.674	9.202	7.612	6.231	9.224
	0.001	0.001	0.001	0.001	0.001	0.001
$ECON_{t-i} \nRightarrow TECH_t$	2.302	1.006	2.344	1.868	1.787	0.618
	0.076	0.39	0.072	0.134	0.13	0.604
$I_{up,t-i} \nRightarrow ECON_t$	11.631	11.941	9.779	6.761	6.016	13.541
	0.001	0.001	0.001	0.001	0.001	0.001
$TECH_{t-i} \nRightarrow I_{up,t}$	0.947	1.202	1.123	0.866	3.016	1.541
	0.418	0.308	0.326	0.458	0.014	0.551

Table 3 presents in-sample coefficient estimates and Newey-West adjusted t statistics in the top half of the table. χ^2 and probability values (presented below) jointly tests the restriction that both $TECH_{t-1} = TECH_{t-1} * I_{up,t-1} = 0$. The adjusted R^2 in row 4 is for the model with $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1}$, and the R^2 below it excludes the technical indicators. Row 5 presents the adjusted R^2 for the model that allows different constants and AR coefficients depending on $I_{up,t-1}$. χ^2 in row 6 tests whether the constant and AR coefficients are identical across different market regimes. The bottom half of the table tests Granger Causality, where the F statistics and Prob. values are reported. $EG, IPG, PIG, SALEG$, $\triangle CU, DIF$, and REC are employment growth, industrial production growth, real personal income growth, real sales growth, diffusion index, differenced capacity utilization and recession, respectively. The constant and lagged AR estimates are not reported for conciseness.

Table 4: **Out of Sample Results for Coincident Indicators**

VAR	EG_t	IPG_t	PIG_t	$SALEG_t$	DIF_t	$\triangle CU_t$
$h = 1$						
$TECH_{t-1}$	2.390	3.489	2.317	2.317	2.904	2.400
	0.008	0.000	0.010	0.010	0.002	0.008
$TECH * I_{up,t-1}$	1.480	-0.037	0.966	0.966	-0.091	0.247
	0.069	0.515	0.167	0.167	0.536	0.402
Both	2.310	3.098	2.164	2.164	2.412	1.994
	0.010	0.001	0.015	0.015	0.008	0.023
$h = 3$						
$TECH_{t-1}$	4.484	4.361	4.563	3.770	5.207	4.339
	0.001	0.001	0.001	0.001	0.001	0.001
$TECH_{t-1} * I_{up,t-1}$	2.686	3.334	2.324	0.994	1.261	2.285
	0.004	0.000	0.010	0.160	0.104	0.011
Both	4.346	4.514	4.378	3.236	4.944	4.130
	0.001	0.001	0.001	0.001	0.001	0.001
$h = 6$						
$TECH_{t-1}$	5.433	4.894	5.556	5.332	7.720	5.377
	0.001	0.0010	0.001	0.001	0.001	0.001
$TECH_{t-1} * I_{up,t-1}$	3.009	3.332	3.869	3.932	3.799	3.468
	0.001	0.000	0.001	0.001	0.001	0.001
Both	5.388	4.999	5.591	5.349	7.641	5.266
	0.001	0.0010	0.001	0.001	0.001	0.001

Table 4 presents out-of-sample results using forecasts from lagged technical indicators $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1}$. We present Clark West adjusted $tstats$ and $Prob.values$. Both averages both forecasts. Results are for horizon $1, 3$, and 6 months ahead. $EG, IPG, PIG, SALEG$, $\triangle CU, DIF$, and REC are employment growth, industrial production growth, real personal income growth, real sales growth, differenced capacity utilization, diffusion index and recession, respectively.

Table 5: **In-Sample and Granger Causality Tests for Leading Indicator Components**

VAR	ORD	ORDN	HRS	BP	CEXP	CLA	ISM
$TECH_{t-1}$	2.008	3.298	0.242	4.492	226.685	-0.068	3.298
	4.645	4.293	5.240	3.754	3.282	-6.427	4.356
$TECH_{t-1} * I_{up,t-1}$	-1.511	-2.166	-0.114	-4.460	-206.565	0.065	-2.297
	-2.379	-1.894	-1.617	-2.636	-1.995	4.491	-1.931
χ^2	21.030	35.770	39.630	8.940	11.210	45.330	24.650
	0.001	0.001	0.001	0.010	0.004	0.001	0.000
R^2	0.061	0.209	0.505	0.021	0.209	0.071	0.779
	0.021	0.171	0.480	0.001	0.171	0.000	0.769
R^2	0.086	0.227	0.878	0.024	0.922	0.081	0.979
χ^2	13.690	10.070	8.831	4.590	11.802	5.510	3.730
	0.008	0.039	0.065	0.129	0.019	0.063	0.152
$TECH_{t-i} \not\Rightarrow ECON$	8.756	10.674	9.202	7.612	7.654	13.135	13.057
	0.001	0.001	0.001	0.001	0.001	0.001	0.001
$ECON_{t-i} \not\Rightarrow TECH$	2.302	1.006	2.344	1.868	1.668	0.875	1.724
	0.076	0.390	0.072	0.134	0.173	0.417	0.179
$I_{up,t-i} \not\Rightarrow ECON$	11.631	11.941	9.779	6.761	6.165	16.047	20.080
	0.000	0.000	0.000	0.000	0.539	0.254	0.000
$TECH_{t-i} \not\Rightarrow I_{up,t-i}$	0.947	1.202	1.123	0.866	1.426	1.192	0.157
	0.418	0.308	0.326	0.458	0.234	0.304	0.692
$ECON_{t-1}$	-0.249	-0.064	-0.961	-0.463	-0.313	-0.325	-0.298
	-3.668	-0.541	-12.622	-5.432	-5.739	-5.082	-5.394
$TECH_{t-1}$	0.012	0.110	0.247	0.042	1.606	-6.531	-0.142
	2.92	4.63	3.87	2.82	2,108	-1.801	-0.172
$ECON_{t_1}$	0.385	-0.616	0.004	0.357	0.674	0.583	0.474
	3.275	-12.65	0.091	4.08	6.668	8.183	4.802
$TECH_{t-1}$	0.004	0.090	0.075	-0.016	0.814	-12.201	3.859
	0.564	0.007	1.91	-1.056	0.787	-2.282	2.782

Table 5 presents in-sample estimates and Newey-West adjusted t statistics in the top half of the table. The χ^2 and probability jointly tests the restriction that both $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1} = 0$. The adjusted R^2 in row 4 are for the model with $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1}$, and the R^2 excludes the technical indicators. The adjusted R^2 in row 5 is for the model that allows different constants and AR coefficients depending on $I_{up,t-1}$. The χ^2 in row 6 tests whether the constant and AR coefficients are identical across regimes. The middle section of the table tests Granger Causality, where the F statistic and Prob. values are reported. AIC criteria determine lag lengths. The bottom half presents a Markov Switching model where $I_{up,t-1}$ determines the regimes. For conciseness, we do not report the full model and instead report only the $ECON_{t_1}$ and $TECH_{t-1}$ estimates and t statistics. Probability parameters are all significant and are available upon request. $ORD, ORDN, HRS, BP, CEXP, CLA$, and ISM are the Conference Board's manufacturing (mfr) new orders, mfr new orders nondefense capital goods, average hours mfr, building permits, consumer expectations, average weekly initial claims, and order's diffusion index.

Table 6: **Out-of-Sample Results for Leading Indicator Components**

VAR	ORD	ORDN	HRS	BP	CEXP	CLA	ISM
$TECH_{t-1}$	1.849	2.034	2.248	2.821	1.847	2.986	1.936
	0.032	0.021	0.012	0.002	0.032	0.001	0.026
$TECH_{t-1} * I_{up,t-1}$	0.534	0.521	0.922	0.682	1.140	-0.519	1.305
	0.297	0.301	0.178	0.248	0.127	0.698	0.096
Both	1.462	1.794	1.792	2.661	1.793	2.423	1.925
	0.072	0.036	0.037	0.004	0.037	0.008	0.027
$TECH_{t-1}$	3.104	3.288	3.974	3.660	2.739	1.405	2.691
	0.001	0.001	0.000	0.000	0.003	0.080	0.004
$TECH_{t-1} * I_{up,t-1}$	0.366	1.183	1.986	0.577	0.179	-1.101	0.012
	0.357	0.118	0.024	0.282	0.429	0.864	0.495
Both	2.637	2.978	3.317	3.577	2.882	0.935	2.203
	0.004	0.001	0.000	0.000	0.002	0.175	0.014
$TECH_{t-1}$	4.365	4.117	5.227	3.774	2.720	0.659	3.251
	0.001	0.001	0.001	0.001	0.003	0.255	0.001
$TECH_{t-1} * I_{up,t-1}$	2.766	2.400	2.945	1.338	0.380	0.149	0.830
	0.003	0.008	0.002	0.090	0.352	0.441	0.203
Both	4.258	3.991	4.686	3.777	2.718	0.545	3.012
	0.001	0.001	0.001	0.001	0.003	0.293	0.001

Table 6 presents out-of-sample results using forecasts from lagged technical indicators $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1}$. We present Clark West adjusted $tstats$ and $Prob.values$. Both averages both forecasts. Results are for horizon $1, 3$, and 6 months ahead. $ORD, ORDN, HRS, BP, CEXP, CLA, andISM$ are the Conference Board's manufacturing new orders, manufacturing new orders nondefense capital goods, average hours manufacturing, building permits, consumer expectations, average weekly initial claims, and order's diffision index.

Table 7: **In-Sample and Granger Causality Tests for Financial Variables**

VAR	SR	YD	M2G	DFR	VOL	NTIS	Stress	LEI
$TECH_{t-1}$	2.520	-0.233	0.000	0.121	-0.040	-0.003	-0.544	0.282
	2.368	0.107	-0.336	3.257	-0.287	1.143	-2.296	3.173
$TECH_{t-1} * UD_{t-1}$	-4.444	0.194	0.001	-0.123	0.626	0.006	0.577	-0.227
	-3.215	0.157	0.938	-2.795	2.798	1.665	2.440	-2.099
χ^2	10.530	4.980	1.230	10.640	14.100	16.923	6.687	10.55
	0.005	0.083	0.540	0.005	0.001	0.000	0.035	0.005
R^2	0.015	0.098	0.353	0.911	0.890	0.028	0.916	0.468
	0.000	0.091	0.354	0.908	0.888	0.000	0.911	0.461
R^2	0.013	4.980	0.362	0.911	0.891	0.028	0.916	0.502
χ^2	0.060	0.097	13.00	3.967	29.020	3.820	3.230	49.955
	0.801	1.290	.005	0.138	0.000	0.050	0.357	0.001
$TECH_{t-i} \not\Rightarrow ECON_t$	0.004	2.034	0.090	12.227	3.932	6.830	7.049	7.892
	0.949	0.088	0.914	0.001	0.009	0.001	0.001	.0001
$ECON_{t-i} \not\Rightarrow TECH$	1.829	0.219	0.115	1.790	1.092	1.726	1.704	5.188
	0.177	0.928	0.891	0.182	0.354	0.181	0.184	0.0004
$I_{up,t-i} \not\Rightarrow ECON$	1.167	2.949	1.416	0.620	1.360	4.900	1.704	5.266
	0.280	0.020	0.243	0.539	0.254	0.008	0.184	.0001
$TECH_{t-i} \not\Rightarrow I_{up,t}$	7.572	0.983	1.831	9.255	4.624	3.182	5.059	3.908
	0.006	0.416	0.161	7.612	0.000	0.042	0.007	0.0038

Table 7 presents in-sample estimates and Newey-West adjusted t statistics in the top half of the table. The χ^2 and probability jointly tests the restriction that both $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1} = 0$. The adjusted R^2 in row 4 are for the model with $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1}$ and without the technical indicators. The adjusted R^2 in row 5 is for the model that allows different constants and AR coefficients depending on whether the market is UP or down the last 200 days. The χ^2 in row 6 then tests whether the constant and AR coefficients are the same across regimes. The bottom half of the table tests Granger Causality, where the F statistic and Prob. values are reported. SR, YD, M2G,DFR,VOL,NTIS, Stress and LEI are stock return, yield curve, money growth, default rate (AAA-BAA), net stock issuance, St. Louis Financial Stress Index and Leading Economic Indicator.

Table 8: **Out-of-sample Results for Financial Variables**

VAR	SR	YD	M2	DFR	VOL	NTIS	Stress	LEI
$TECH_{t-1}$	2.821	1.847	2.986	1.849	2.034	1.936	2.248	3.318
	0.002	0.032	0.001	0.032	0.021	0.026	0.012	0.0004
$TECH_{t-1} * I_{up,t-1}$	0.682	1.140	-0.519	0.534	0.521	1.305	0.922	0.414
	0.248	0.127	0.698	0.297	0.301	0.096	0.178	0.339
Both	2.661	1.793	2.423	1.462	1.794	1.925	1.792	2.992
	0.004	0.037	0.008	0.072	0.036	0.027	0.037	0.001
$TECH_{t-1}$	3.660	2.739	1.405	3.104	3.288	2.691	3.974	2.554
	0.000	0.003	0.080	0.001	0.001	0.004	0.001	0.005
$TECH_{t-1} * I_{up,t-1}$	0.577	0.179	-1.101	0.366	1.183	0.012	1.986	-2.405
	0.282	0.429	0.864	0.357	0.118	0.495	0.024	0.992
Both	3.577	2.882	0.935	2.637	2.978	2.203	3.317	2.121
	0.000	0.002	0.175	0.004	0.001	0.014	0.001	0.017
$TECH_{t-1}$	3.774	2.720	0.659	4.365	4.117	3.251	5.227	2.141
	0.000	0.003	0.255	0.000	0.000	0.001	0.001	0.016
$TECH_{t-1} * I_{up,t-1}$	1.338	0.380	0.149	2.766	2.400	0.830	2.945	-2.341
	0.090	0.352	0.441	0.003	0.008	0.203	0.002	0.990
Both	3.777	2.718	0.545	4.258	3.991	3.012	4.686	1.496
	0.000	0.003	0.293	0.001	0.001	0.001	0.001	0.067

Table 8 presents out-of-sample results using forecasts from the lagged technical indicators $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1}$. Both averages both forecasts. Results are for horizon $1, 3$, and 6 months ahead. SR, YD, M2G,DFR,VOL,NTIS, Stress and LEI are stock return, yield curve, money growth, default rate (AAA-BAA), net stock issuance, St. Louis Financial Stress Index and Leading Economic Indicator.

Table 9: **In-Sample and Granger Causality Results for Quarterly Variables**

VAR	RGDPG	INVTG	PROFG	ATPROFG	PFNIG	DIVG
$TECH_{t-1}$	0.012	0.067	0.073	0.120	0.011	0.046
	4.584	4.555	3.025	4.058	3.607	4.188
$TECH_{t-1} * I_{up,t-1}$	-0.011	-0.047	-0.067	-0.115	-0.009	-0.028
	-2.875	-2.151	-2.107	-2.448	-2.010	-1.687
χ^2	23.490	29.878	9.190	17.020	16.630	21.550
	0.000	0.000	0.010	0.000	0.000	0.000
R^2	0.217	0.159	0.032	0.068	0.141	0.136
	0.140	0.043	-0.004	0.000	0.072	0.054
R^2	0.952	0.155	-0.004	0.084	0.147	0.241
χ^2	3.660	1.135	4.571	9.450	3.420	30.440
	0.157	0.576	10.110	0.009	0.141	0.000
$TECH \not\Rightarrow ECON$	5.096	9.175	6.705	9.350	13.230	4.231
	0.001	0.000	0.010	0.003	0.000	0.003
$ECON \not\Rightarrow TECH$	1.645	1.335	0.080	0.154	1.820	0.487
	0.164	0.258	0.777	0.695	0.177	0.746
$UD \not\Rightarrow ECON$	10.191	7.727	5.141	7.403	18.370	3.550
	0.000	0.000	0.024	0.007	0.000	0.008
$TECH \not\Rightarrow UD$	0.615	0.251	0.748	1.111	1.220	0.296
	0.542	0.909	0.388	0.293	0.340	0.880

Table 9 presents in-sample estimates and Newey-West adjusted t statistics in the top half of the table. The χ^2 and probability jointly tests the restriction that both $TECH_{t-1}$ and $TECH_{t-1} * I_{up,t-1} = 0$. The adjusted R^2 in row 4 are for the model with $TECH_{t-1}$ and $TECH_{t-1} * UD_{t-1}$ and without the technical indicators. The adjusted R^2 in row 5 is for the model that allows different constants and AR coefficients depending on whether the market is UP or down the last 200 days. The χ^2 in row 6 then tests whether the constant and AR coefficients are the same across regimes. The bottom half of the table tests Granger Causality, where the F statistic and Prob. values are reported. RGDPG, INVTG, PROFG, ATPROFG, PFNIG, and DIVG are real GDP, investment, profits, after-tax profits, private nonresidential fixed investment growth, and dividend growth. All variables are real.

Table 10: **Out-of-sample results for Quarterly Variables**

VAR	RGDPG	INVTG	PROFG	ATPROFG	PFNIG	DIVG
$TECH_{t-1}$	2.597	2.266	1.328	1.637	2.717	1.890
	0.005	0.012	0.092	0.051	0.003	0.029
$TECH_{t-1} * I_{up,t-1}$	1.239	1.008	-0.219	0.154	1.512	0.413
	0.108	0.157	0.587	0.439	0.065	0.340
Both	2.393	2.013	1.005	1.269	2.589	1.425
	0.008	0.022	0.158	0.102	0.005	0.077
$TECH_{t-1}$	2.252	3.075	1.459	2.095	3.401	2.531
	0.012	0.001	0.072	0.018	0.000	0.006
$TECH_{t-1} * I_{up,t-1}$	2.056	1.759	-0.071	0.520	1.700	1.252
	0.020	0.039	0.528	0.302	0.045	0.105
Both	2.390	2.919	1.399	1.871	3.209	2.220
	0.008	0.002	0.081	0.031	0.001	0.013
$TECH_{t-1}$	1.007	1.903	0.872	1.416	2.942	2.888
	0.157	0.028	0.192	0.078	0.002	0.002
$TECH_{t-1} * I_{up,t-1}$	0.207	0.797	0.955	-0.343	1.614	1.310
	0.418	0.213	0.170	0.634	0.053	0.095
Both	0.953	1.721	0.925	1.244	2.776	2.713
	0.170	0.043	0.178	0.107	0.003	0.003

Table 10 presents out-of-sample results using forecasts from lagged technical indicators,$TECH_{t-1}$ and and $TECH_{t-1} * I_{up,t-1}$. Both averages both forecasts. Results are for horizon $1, 3$, and 6 months ahead. RGDPG, INVTG, PROFG, ATPROFG, PFNIG, and DIVG are real GDP, investment, profits, after-tax profits, private nonresidential fixed investment growth, and dividend growth. All variables are real.

Table 11: **Forecasting Recessions**

VAR	$Recess_{h=1}$	$Recess_{h=2}$	$Recess_{h=3}$	$Recess_{h=6}$
$TECH_{t-1}$	-3.940	-4.180	-4.418	-4.539
	-11.443	-11.536	-11.554	-10.123
$TECH_{t-1} * I_{up,t-1}$	0.497	1.133	1.954	2.312
	0.713	1.479	2.334	2.213
	0.399	0.430	0.462	0.480
$TECH_{t-1}$	-4.300	-4.424	-4.570	-4.555
	-10.855	-10.966	-11.005	-9.945
$TECH_{t-1} * I_{up,t-1}$	0.662	1.317	2.098	2.313
	0.916	1.674	2.453	2.240
LIDT	-0.097	-0.087	-0.075	-0.048
	-5.854	-5.065	-4.213	-2.428
	0.478	0.490	0.506	0.498
LIDT	-0.061	-0.057	-0.052	-0.035
	-5.968	-5.431	-4.847	-2.991
	0.073	0.065	0.054	0.026
$TECH_{t-1}$	7.115	7.086	7.031	7.224
	0.001	0.001	0.001	0.001
$TECH_{t-1} * I_{up,t-1}$	7.963	8.191	8.405	9.007
	0.001	0.001	0.001	0.001
Both	7.579	7.627	7.664	7.996
	0.001	0.001	0.001	0.001
$TECH_{t-1}$	7.711	7.498	6.933	6.158
	0.001	0.001	0.000	0.001
$TECH_{t-1} * I_{up,t-1}$	6.124	6.067	5.927	5.440
	0.001	0.001	0.001	0.001
Both	7.057	6.903	6.546	5.867
	0.001	0.001	0.001	0.001

Table 11 presents out-of-sample results using forecasts from lagged the lagged technical indicator,$TECH_{t-1}$ and $TECH * UD_{t-1}$ the lagged technical indicator UP-DOWN indicator. Results for the LEI are also presented. Both averages both forecasts. Results are for horizon $1, 3$, and 6 months ahead.

Table 12: **Out-of-sample R^2 for GDP**

Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$h = 1$	TECH	TECHSR	COMTEC	SIM	DYNFAC	CLUS	COM126	COM125	COM1256	COM1245
1982.1-2010.2	0.116**	0.072**	0.189**	0.132**	0.042**	0.166**	0.235**	0.223**	0.284**	0.277**
1992.1-2011.1	0.078**	0.006	0.168**	0.068**	0.094**	0.056**	0.206**	0.209**	0.255**	0.258**
2000.1-2013.1	0.097**	0.129**	0.239**	0.089**	0.122**	0.069**	0.237**	0.244**	0.263**	0.271**
2007.1-2013.1	0.120**	0.450**	0.397**	0.095**	0.146**	0.088**	0.332**	0.336**	0.334**	0.340**
Fin. Crisis	0.172**	0.754**	0.563**	0.119	0.489**	0.129	0.450**	0.444**	0.488**	0.456**
Recession	0.177	0.612	0.454	0.149	0.452	0.211	0.391	0.474	0.421	0.407
Expansion	0.051	-0.510	-0.097	0.113	-0.400	0.117	0.068	0.071	0.136	0.131
$h = 2$										
1982.1-2010.2	0.165**	0.059*	0.209**	0.131**	-0.045	0.115**	0.237**	0.287**	0.278**	0.281**
1992.1-2011.1	0.087**	-0.006	0.145**	0.049**	-0.130	0.017	0.181**	0.192**	0.192**	0.197**
2000.1-2013.1	0.091**	0.025*	0.158**	0.053*	-0.113	0.019	0.173**	0.165**	0.167**	0.174**
2007.1-2013.1	0.121**	0.438**	0.333**	0.061*	-0.015	0.029	0.262**	0.267**	0.233**	0.241**
Fin. Crisis	0.155**	0.588**	0.412**	0.077	0.261**	0.051	0.314**	0.379**	0.311**	0.316**
Recession	0.217	0.613	0.450	0.128	0.231	0.108	0.352	0.396	0.334	0.324
Expansion	0.097	-0.667	-0.105	0.134	-0.407	0.125	0.088	0.145	0.205	0.195

Table 12 out-of-sample R^2 for forecasting GDP for one and two quarter horizons. TECH uses equation (3) to forecast GDP, while TECHSR uses (8) to construct forecasts of the stock market and then uses these forecasts to predict GDP (equations 9). COMTECH combines the forecasts of both technical forecasts. DYNFAC and Cluster are forecasts constructed using 3 dynamic factors and 3 clusters. COM126, COM125, COM1256 and COM1245 combine/pool the forecasts from columns (1), (2) and (6), etc. Significance levels use Clark and West (2007) $MSFE-adjusted$ statistics.

Table 13: **Appendix I: Markov Switching**

Regime 1							
VAR	EG	IPG	PIG	SALG	DIF	$\triangle$CU	$\triangle$LEI
$ECON_{t-1}$	-0.351	0.038	0.293	-0.432	0.108	-0.007	0.133
	0.098	0.050	0.036	0.080	0.034	0.036	0.061
$ECON_{t-2}$	0.946	0.152	0.134	-0.176	0.076	0.136	0.399
	8.313	3.312	3.889	-2.725	2.038	2.819	6.218
$ECON_{t-3}$	0.364		0.041		0.103	0.132	-0.087
	3.315		1.140		2.942	2.759	-1.402
$TECH_{t-1}$	0.002	0.003	0.002	0.005	3.850	0.259	0.236
	4.034	2.791	2.992	2.610	1.124	2.739	3.193
Regime 2							
$ECON_{t-1}$	0.409	0.879	-1.286	0.331	0.242	0.934	0.366
	8.502	8.099	-11.417	3.232	4.281	8.852	4.400
$ECON_{t-2}$	0.177	0.162	-0.084	0.318	0.113	0.057	0.150
	4.120	1.472	-0.486	3.285	2.091	0.471	1.802
$ECON_{t-3}$	0.138		1.048		0.138	0.196	0.712
	3.070		5.378		2.641	2.336	7.879
$TECH_{t-1}$	1.236	0.554	3.291	2.124	1.368	0.208	-0.859
Prob	-1.882	2.408	3.628	1.133	1.027	2.531	0.782
Parameters	-3.993	3.837	5.914	2.261	6.437	3.241	2.295

The Appendix presents a simple Markov Switching model where we report the coefficients and $Zstats$ (calculated using robust standard errors) for the two regimes. IPG and SLAG use only two autoregressive lags. The last two rows report the Probability parameters and their Z statistics.