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ABSTRACT

Disequilibrating macro shocks affect different firms' prospects differently, increasing idiosyncratic variation in forward-looking stock returns before affecting economic growth. Consistent with most such shocks from 1947 to 2020 enhancing productivity, increased idiosyncratic stock return variation forecasts next-quarter real GDP growth, industrial production growth, and consumption growth both in-sample and out-of-sample. These effects persist after controlling for other leading economic indicators.

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A data appendix is available at http://www.nber.org/data-appendix/w30071

1. Introduction

Macroeconomics associates business cycle fluctuations with exogenous shocks, including technology shocks, which alter the structure of production (Kydland and Prescott 1982). Economic growth theory attributes most economic growth in high-income economies to technological progress, whereby new higher productivity technologies repeatedly displace old lower productivity technologies (Solow 1957; Syverson 2011; Vivarelli 2014). Recent work adds institutional reforms (La Porta *et al.* 2008), financial liberalizations (Henry 2007), and market expansions (Aw *et al*. 2011) to the roster of productivity-enhancing shocks. Work in growth theory (Aghion and Howitt, 1992) and finance (Fogel *et al.* 2008; Faccio and McConnell 2020) associates increased productivity with creative destruction (Schumpeter 1911), wherein innovative firms partially or completely displace established firms.

Black (1981, p. 122) argues that, because investor expectations render stock markets forward-looking, all such shocks are likely to manifest first as elevated idiosyncratic stock returns variation (he terms this decoherence) as stock prices capitalize new information about individual firms' altered prospects in the disequilibrated economy. Black reflects that disequilibrating shocks render previously optimal resource allocation ex-post suboptimal. He therefore argues that higher idiosyncratic variance in stock returns forecasts macroeconomic downturns. In contrast, Schumpeter (1911) argues that most disequilibrating shocks reflect the rollouts of new technologies (or, less often, new markets or institutions) that portend increased productivity. Given the forward-looking nature of stock returns, it follows that "idiosyncrasy" in stock returns forecasts macroeconomic prosperity. Schumpeter's argument is supported by Solow's (1957) findings that productivity-increasing disequilibration has predominated historically in high-income economies.

Recent work attends to both views. Stein and Stone (2013) find uncertainty depresses capital investment but encourages R&D spending. Segal, Shaliastovich, and Yaron (2015) decompose shocks to economic fundamentals into positive and negative components, which they argue forecast economic activity increases and decreases, respectively. Segal and Engstrom (2017), modeling shocks to consumption growth using a bad-environment-good environment specification, match stylized facts of consumption dynamics and asset prices.

Following Black (1981), we adopt idiosyncratic stock return variance as a measure of disequilibration. Our findings support Schumpeter (1911) and Solow (1957): higher current quarter *idiosyncratic variance*, defined as mean squared idiosyncratic stock returns, forecasts higher next quarter and future quarter real growth in GDP, industrial production, aggregate consumption, and investment in innovation over 1947Q1 to 2020Q4.

These results are robust to controlling for other well documented leading indicators of economic conditions: term spreads (Harvey 1988); credit spreads (Gilchrist and Zakrajšek, 2012; López-Salido et al., 2017), change in long-term bond yield (Stock and Watson, 1989), dividend yield (Fama and French, 1988; Chen, 1991), market returns (Fama, 1981; Barro, 1990), inflation (Fischer, 1993; Barro, 1995), and stock market liquidity (Næs, Skjeltorp, and Ødegaard, 2011; Switzer and Picard, 2016). Our results are also robust to alternative ways of decomposing stock return variation into idiosyncratic and systematic components (Carhart, 1997; Campbell et al. 2001) and using the Chicago Fed's National Activity Index as an alternative measure of economic activity. Furthermore, augmenting other leading indicators with idiosyncratic stock return variance significantly improves the performance of forecasting models. Also, while bidirectional causality can affect these other indicators (e.g., Hamilton and Lin 1996; Choudhry et al. 2016), Granger causality tests show idiosyncratic stock return variance forecasts economic

activity and reject the converse. Finally, our findings are not driven by mean reversion in aggregate output.

We then explore channels through which disequilibrating shocks affect future economic growth. One possibility is that idiosyncratic stock returns variation signals disequilibration that leads to counter-cyclical government spending. Bansal, Croce, Liao and Rosen (2019) show that increased uncertainty reallocates resources from the private sector to government. However, higher idiosyncratic stock returns variance does not forecast growth in government spending.

Another possibility is that disequilibration alters households-level wealth and might thereby affect aggregate consumption. Herskovic, Kelly, Lustig, and Van Niewerburgh (2016) argue elevated idiosyncrasy in stock returns can affect consumption by changing households' incomes, assets, and risk exposures. They conclude, "The connection between firm-level volatility, household-level risk, and asset prices established in our paper suggests that CIV (common idiosyncratic volatility) is a plausible proxy for dispersion in consumption growth." We find higher idiosyncratic stock returns variance forecasts higher next-quarter aggregate consumption. We posit that increased dispersion in households' human and portfolio capital leads to increased aggregate consumption because positive shocks rapidly increase household consumption (Agarwal and Qian 2014) but behavioral biases delay decreases in household consumption after negative shocks (Ganong and Noel 2019).

A third possibility is that disequilibration might forecast growth in aggregate investment. Most directly, firms favored by a disequilibrating shock might increase investment while disfavored firms might disinvest. Bachmann and Bayer (2014) find cross-sectional dispersion in firm investment to be contemporaneously procyclical. However, the irreversibility of corporate investment decisions and real options theory complicate this simple prediction. Increased

idiosyncratic risk can hasten or delay investments (Liu and Wang 2021). Real option investment timing can depend on firms' default risk (Chang, d'Avrnas, and Eisfeldt 2021), investment payoff structures (Miao and Wang 2007), and the frequency of technology shocks (Leippold and Stromberg 2017). Elevated risk can also rebalance firms' investments away from property, plant and equipment and towards investment in innovation (Stein and Stone 2013). We find that higher idiosyncratic stock returns variation does not forecast increased aggregate investment.

A fourth possibility is that disequilibration might forecast growth in intangible investment, rather than the tangible investment in national income accounts. Consistent with this, we find higher idiosyncratic stock returns variation forecasts higher next-quarter growth in patent applications, patent citations, total factor productivity, and labor productivity.

These findings combine to confirm the deep connection between disequilibrating technology shocks and economic growth that motivates this study. Our results are consistent with elevated idiosyncratic stock returns variation:

1. Being a valid proxy for a disequilibrating shock because intrinsically forward-looking stock prices change to reflect the altered prospects of different firms, both for possible disequilibrium quasi-rents and for being poorly situated in the new equilibrium.
2. Forecasting higher next-quarter growth in aggregate output and investment in innovation because disequilibrating shocks most often reflect technological progress and creative destruction.
3. Forecasting higher next-quarter growth in aggregate consumption because disequilibrating shocks alter the distribution of human and portfolio capital, with positively impacted households increasing their consumption and negatively affected households delaying decreasing their consumption.

We welcome future work that might offer other interpretations of our findings.

2. Variables Definition and Data Summary

The sample includes all common stocks listed on the NYSE, Nasdaq, and Amex from January 1, 1947 to December 31, 2020. The data begin in 1947 because this is when quarterly GDP growth series become available. Appendix A lists detailed variable definitions and sources of the data.

2.1 Measures of Stock Returns Idiosyncrasy and Macroeconomic Growth

Stock return variation is decomposed into a systematic and a firm-specific component using the regression (Roll 1988; Morck et al. 2000)

$$R_{j,s} = \alpha_{j,t} + \beta_{j,t} R_{m,s} + \varepsilon_{j,s} \quad [1]$$

where $R_{j,s}$ is the return of stock *j* on day *s*, $R_{m,s}$ is the value-weighted market return on day *s*, and *t* is a quarter subscript. Stock *j*'s own return is excluded from the calculations of its market return.

Our primary idiosyncrasy measure is *aggregate idiosyncratic variation* in stock returns, AIV_t, defined as the value-weighted cross-section mean of the sum of squared variances of the errors from all stock-level time-series regressions [1]. That is, firm-level idiosyncratic variation $SSE_{j,t} \equiv \frac{1}{N_{j,t}-1} \sum_{s \epsilon t} \varepsilon_{j,s}^2$ is estimated using returns for stock *j* in all trading days *s* in quarter *t*. $N_{j,t}$ is the number of daily return observations for stock *j* in quarter *t*. Aggregate idiosyncratic variation is the value-weighted cross-sectional mean of the firm-level $SSE_{j,t}$ each quarter

$$AIV_t \equiv \sum_j w_{j,t} SSE_{j,t} \quad [2]$$

where $w_{j,t}$ is market capitalization of stock *j* at the beginning of quarter *t* as a fraction of the total market capitalization of stocks. A larger value of AIV_t indicates that stocks are moving more idiosyncratically in quarter *t*.

We define *aggregate systematic variation*, ASV_t, analogously. We first define $SSM_{j,t}$ as the sum of squared variation explained by the time-series regression model [1] for firm *j* estimated using all trading days *s* in quarter *t*. *Aggregate systematic variation* is the value-weighted cross-sectional mean of the firm-level $SSM_{j,t}$ each quarter

$$ASV_t \equiv \sum_{\mathrm{j}} w_{j,t} SSM_{j,t} \qquad [3]$$

A larger ASV_t means market-wide movements pull individual stocks along to a greater extent in quarter *t*. Some tests use relative idiosyncrasy, aggregate idiosyncratic over systematic variation in stock returns, defined as $\psi_t \equiv AIV_t / ASV_t$.

The tests below forecast next-quarter macroeconomic growth rates, defined as log differences in real GDP, $\Delta \ln GDP_{t+1}$, or real industrial production, $\Delta \ln IP_{t+1}$. The forecasting variables of primary interest in these tests are natural logarithms of aggregate idiosyncratic variation, $\ln AIV_t$, or relative idiosyncratic variation, $\ln \psi_t \equiv \ln AIV_t - \ln ASV_t$.

2.2 Controlling for Other Leading Indicators

Variables found elsewhere to predict economic conditions, measured quarterly, are: (i) change in credit spread, ΔS_t, the change in the premium of Baa industrial bond yield over ten-year T- bond yield (López-Salido et al., 2017; Bordalo, Gennaioli, and Shleifer, 2018; Chang, d'Avernas, and Eisfeldt, 2021); (ii) term spread, $TERM_t$, the ten-year T-bond yield minus the three-month T-bill rate (Harvey, 1988; Estrella and Hardouvelis, 1991); (iii) ΔTB_t, the change in ten-year T-bond yield (Stock and Watson, 1989; Estrella and Mishkin 1998; Diebold, Rudebusch, and Aruoba, 2006); (iv) dividend yield, DIV_t, the quarterly cumulative dividend yield of the value-weighted CRSP stock portfolio (Fama and French, 1989; Chen, 1991); (v) the excess market return, RET_t, the value-weighted CRSP market index return minus the three-month T-bill yield (Fama, 1981;

Barro, 1990); (vi) inflation, INF_t, the quarterly percentage change in the Consumer Price Index (CPI) (Fischer 1993; Barro, 1995); and (vii) stock market illiquidity, $ILLIQ_t$, the equal-weighted mean Amihud (2002) illiquidity measure (absolute return divided by the dollar volume) across all common stocks (Næs, Skjeltorp, and Ødegaard, 2011; Switzer and Picard, 2016) and stock market volatility (Schwerz, 1989; Bloom, 2009), ln ASV_t, defined as in [2].[1]

2.3 Data Summary

Figure 1 graphs quarterly aggregate idiosyncratic, AIV_t and systematic, ASV_t, variation from 1926Q1-2020Q4, the shaded areas indicating NBER recessions. Both measures move counter-cyclically. Two patterns deserve notice. First, the most prominent variation spikes appear in the two highest amplitude business cycles of the past century: the 1920s-1930s and 1990s-2000s. The first decade of each episode contains an unusually large and sustained economic boom driven by new technology; the second decade of each contains an unusually deep and prolonged downturn subsequent to a major financial crisis. This suggests a non-trivial statistical relationship. Second, quarterly ASV_t and AIV_t co-move, so relative idiosyncratic variation, $\psi_t = ASV_t/AIV_t$, gauges shifts in their relative magnitudes.

Figure 2 plots relative idiosyncratic variation, ψ_t, over the same period. Visually, the ratio rises in expansions, drops preceding recessions, and remains low during recessions. Relative idiosyncratic variation is high in economic booms – notably, the 1920s, 1950s-1960s, and the 1990s – and low in busts – the double-dip downturns (1930 to 35 and 1937 to 39) of the Great Depression, the 1970s and early 1980s stagnation, and the moderated growth period following the dot.com crash of 2000, especially the recessions of 2008-2009 and early 2020.

[1] All variables pass the Dickey Fuller Generalized Least Squares unit root test (DF-GLS), except for stock market illiquidity. The first-order differenced illiquidity series is used in subsequent tests.

Table I reports summary statistics for the stock returns variation measures, macroeconomic growth rates, and control variables over the sample period 1947Q1-2020Q4. Table II confirms that systematic and idiosyncratic variations are highly correlated ($\rho = 70.6\%$, $p < 0.01$). Both also correlate significantly and negatively with next-quarter macroeconomic growth, though systematic variation has a larger negative correlation with both macroeconomic growth measures. Consequently, the relative idiosyncratic variation correlates positively and significantly with next-quarter macroeconomic growth ($\rho = 27.6\%$ $p < 0.01$ with GDP growth, $\rho = 30.2\%$ $p < 0.01$ with industrial production growth). The control variables credit spread (ΔS), term spread (*TERM*), excess market return (*RET*), market liquidity (*ILLIQ*), and systematic volatility (ln *ASV*) all correlate significantly with the next-quarter macroeconomic indicators in directions consistent with prior studies (Stock and Watson 1989; Schwerz, 1989; Næs et al., 2011; López-Salido et al., 2017).

3. Predicting Economic Growth with Stock Returns Idiosyncrasy

This section first shows that stock returns idiosyncrasy predicts subsequent macroeconomic growth. The results are robust to alternative decomposition of stock return variation into idiosyncratic and systematic components (*AIV* and *ASV*) and to Chicago Fed's National Activity Index (*CFNAI*) as an alterative measure of economic growth. Then, this section reports Granger causality tests showing that predictability is unidirectional: idiosyncrasy predicts macroeconomic growth, but macroeconomic growth does not predict idiosyncrasy. Lastly, the section presents out-of-sample tests that show returns idiosyncrasy improves forecasting accuracy in simple models predicting future macroeconomic growth.

3.1 Baseline Next Quarter Predictive Regressions

Table III summarizes results from our baseline regression [4] for testing how well stock return idiosyncrasy in quarter *t* predicts macroeconomic growth in quarter *t* + 1,

$$\Delta \ln Y_{t+1} = a + b \ln AIV_t + b_1 \Delta S_t + b_2 TERM_t + b_3 \Delta TB_t + b_4 DIV_t + b_5 RET_t \quad [4]$$
$$+ b_6 INF_t + b_7 ILLIQ_t + b_8 \ln ASV_t + b_9 \Delta \ln Y_t + e_t$$

where macroeconomic growth $\Delta \ln Y_{t+1}$ is $\ln Y_{t+1} - \ln Y_t$ with Y either *GDP* or *IP* and the explanatory variables as defined in 2.2.

Panel A reports regression results and p-levels for Newey-West (1987) significance tests.[2] Our baseline results, regressions 3A.1 and 3A.2, show higher current-quarter ln AIV_t predicting statistically and economically significantly faster next-quarter growth in real GDP and real industrial production using data the whole same period of 1947Q1 to 2020Q4. Specifically, a one standard deviation increase in current-quarter ln AIV_t predicts 0.182 percentage points faster real GDP growth (roughly one-quarter of is 0.76% per quarter mean) and 0.206 percentage points faster real industrial production growth (one-third of its 0.67% per quarter mean) the next quarter.

3.2 Rejecting Econometric Artifacts

Before proceeding further, we confirm that econometric artifacts do not explain Table III. To save space, some tests in this section are tabulated in the Appendix.

First, the Table III regressions contain a full roster of alternative leading indicators. The control variable coefficients in 3A.1 and 3A.2 show lower credit spread, ΔS_t, and higher excess market returns, RET_t, this quarter predicting faster next-quarter real GDP and industrial

[2] The coefficients of ln *AIV* and ln*(AIV/ASV)* reported in this and subsequent predictive regressions of GDP and industrial production growth are regression coefficients multiplied by 100 to express relationships to percentage point changes in the left-hand side variable. In all regressions in Table III, ln AIV_t and ln ASV_t are jointly significant.

production growth.[3] Ln AIV_t attracts a robustly positive coefficient, consistent with this variable having unique forecasting traction. The uniformly significant negative coefficients on the natural logarithms of aggregate systematic variation, ln ASV_t, stands out as consistent with prior work associating higher macro-level uncertainty with macro downturns (e.g., Bernanke 1983; Romer 1990; Bloom 2009; Alfaro, Bloom, and Lin 2018; Alessandri and Mumtaz 2019). However, the high correlation of lnAIV_t with ln ASV_t ($\rho = 0.706,\ p < 0.01$) in Table II raises the concern that multicollinearity bias might underlie positive coefficients in the former and negative coefficients in the latter. Rejecting this explanation, Hausman tests dropping ln AIV_t from the regressions in Table III confirm its significant contribution across all specifications. We conclude elevated stock return idiosyncrasy contributes uniquely to predicting next-quarter output growth.

A second concern is mean-reversion in output growth. Table III also shows the coefficient of current output growth $\Delta \ln Y_t$ is either insignificant, or marginally positively significant, depending on the specification; so next-quarter output growth is not mean-reverting in general. Nonetheless, if elevated idiosyncratic volatility shock lowered contemporaneous output growth, which then reverted to its mean one quarter later, idiosyncratic variation would spuriously appear to predict higher next quarter growth in Table III. Appendix Table A1 Panel A shows GDP and industrial production growth indeed correlate negatively with contemporaneous idiosyncratic (ln *AIV*) and systematic variations (ln *ASV*). However, the latter negative correlation is far larger, leaving the ratio of idiosyncratic to systematic variation, expressed as $\ln \psi_t$, positively correlated with both contemporaneous growth measures. Appendix Table A1 Panel B summarizes regressions analogous to [4], but explaining contemporaneous $\Delta \ln Y_t$, rather than forecasting next-quarter $\Delta \ln Y_{t+1}$. In these, ln ASV_t attracts a significant negative coefficient,

[3] Dropping some of the control variables weakens the statistical significance, but the coefficient of ln AIV_t remains significant in the regressions predicting GDP growth.

consistent with high systematic volatility in downturns; however, ln AIV_t attracts a positive insignificant coefficient. This is inconsistent with mean-reversion driving the results in Table III. Finally, if high ln AIV_t caused output growth to fall in quarter t and rebound in $t+1$, the variable would not attract a positive coefficient in regressions analogous to Table III but forecasting current-plus-next-quarter output growth, $\Delta \ln Y_{t+1} + \Delta \ln Y_t$. Inconsistent with mean-reversion driving our findings Appendix Table A1 Panel C shows ln AIV_t attracting a significant positive coefficient in these tests.

3.3 Robustness to Alternative Stock Return Variance Decomposition

The decomposition of stock return variation described in section 2.1 is simple and follows Morck et al. (2000) and numerous other papers that use their methodology. This section shows that other decompositions used in the literature yield very similar results to those in the baseline regressions 3A.1 and 3A.2.

One alternative decomposition uses Carhart's four-factor model

$$R_{j,s} - R_{f,s} = \alpha_{j,t} + \beta_{j,t}\left(R_{M,s} - R_{f,s}\right) + s_{j,t}SMB_s + h_{j,t}HML_s + m_{j,t}UMD_s + \epsilon_{j,s}, \qquad [5]$$

where $R_{j,s}$ is the return of stock j on day s, $R_{m,s}$ the value-weighted market return on day s, $R_{f,s}$ the risk-free rate, SMB_s, HML_s, and UMD_s the risk-factor on day s for size, book-to-market, and momentum, respectively. The variation in [5], rather than in [1], is then decomposed into idiosyncratic (AIV_t) and systematic variation (ASV_t) using [2] and [3]. Regressions 3A.3 and 3A.4 repeat the baseline regressions 3A.1 and 3A.2 using these alternative versions of the two variables. The results are virtually identical.

A second approach by Campbell *et al*. (2001) decomposes firms' stock return variation into three components: aggregate market (ASV_t), primary industry (APV_t), and idiosyncratic variation (AIV_t), defined as:

$$ASV_t = \sum_{s\in t}\left(R_{m,s} - \bar{R}_{m,t}\right)^2$$

$$APV_t = \sum_i w_{i,t} \sum_{s\in t}\left(R_{i,s} - R_{m,s}\right)^2 \qquad [6]$$

$$AIV_t = \sum_j w_{j,t} \sum_{s\in t}\left(R_{j,s} - R_{i,s}\right)^2,$$

where $R_{m,s}$ is the value-weighted market index return on day s, $\bar{R}_{m,t}$ is the average daily market index return in quarter t, $R_{i,s}$ is the return of two-digit SIC industry i on day s, and $R_{j,s}$ is the return of firm j in industry i on day s. Regressions 3A.5 and 3A.6 repeat the baseline regressions 3A.1 and 3A.2 using this definition of AIV_t and controlling for both ASV_t and APV_t. The results are virtually identical to the baseline regressions.

A third approach, described in section 3.1 and following Morck et al. (2000), uses the natural logarithms of relative idiosyncratic variation, $\ln \psi_t$. Panel B of Table III reruns each Panel A regression, but summarizes results from our baseline regression [4] for testing how well relative idiosyncratic variation in quarter t predicts macroeconomic growth in quarter $t + 1$,

$$\Delta \ln Y_{t+1} = a + b \ln \psi_t + b_1 \Delta S_t + b_2 TERM_t + b_3 \Delta TB_t + b_4 DIV_t + b_5 RET_t \qquad [7]$$
$$+ b_6 INF_t + b_7 ILLIQ_t + b_9 \Delta \ln Y_t + e_t$$

where all variables are as in [4]. This constrains the coefficient of $\ln AIV_t$ to be minus one times that of $\ln ASV_t$, but conserves a degree of freedom. The result is uniformly better regression fits. The coefficients of $\ln \psi_t$ are uniformly positive and significant, consistent with a rise in idiosyncratic relative to systematic variation in stock returns predicting faster next quarter growth.

3.4 Robustness to Alternative Measure of Economic Activity

The tests above all use stock returns idiosyncrasy to predict either GDP growth or industrial production growth. This section repeats these exercises, but predicting an alternative measure of

economic prosperity.

The Chicago Fed's National Activity Index (*CFNAI*) is a monthly comprehensive economic activity index based on 85 economic activity series. A three-month moving average of *CFNAI* tracks economic expansions and contractions (Evans, Liu, and Pham-Kanter, 2002; Berge and Jordà 2011), and thus provides an alternative to GDP growth and industrial production growth for measuring macroeconomic activity.[4] Our quarterly variable $CFNAI_t$ is, therefore, the equal-weighted average of *CFNAI* across the three months in quarter *t*. These data are available quarterly from 1967Q2 to 2020Q4.

Table IV summarises regressions using idiosyncratic variation (ln *AIV*) to predict next-quarter values of the *CFNAI* index. The odd-numbered regressions show higher idiosyncratic variation, measured by the baseline model, the Carhart (1997) four-factor model, or the Campbell et al (2001) model predicts higher national economic activity. The even-numbered regressions repeat this exercise measuring idiosyncratic variation by the ratio of idiosyncratic to systematic return variation, $\ln \psi_t$. This ratio significantly predicts *CFNAI* across all three specifications.

3.5 Granger Causality Tests

Granger causality test examines whether the lags of stock returns idiosyncrasy are jointly significant in predicting economic growth, and in turn whether the lags of the economic growth measures are jointly significant in predicting stock returns idiosyncrasy, as shown in the vector autoregressions (VARs) below:

$$\Delta \ln Y_t = \alpha + \sum_{i=1}^{k} \delta_{t-i} \Delta \ln Y_{t-i} + \sum_{i=1}^{k} \beta_{t-i} \ln AIV_{t-i} + \sum_{i=1}^{k} \gamma_{t-i} X_{t-i} + \epsilon_t \quad [8]$$

$$\ln AIV_t = \alpha + + \sum_{i=1}^{k} \delta_{t-i} \Delta \ln Y_{t-i} + \sum_{i=1}^{k} \beta_{t-i} \ln AIV_{t-i} + \sum_{i=1}^{k} \gamma_{t-i} X_{t-i} + \epsilon_t \quad [9]$$

[4] The *CFNAI* data are available at https://www.chicagofed.org/publications/cfnai/index

where $Y = GDP$ or IP and X denotes the set of established predictors of economic growth and their lags: change in credit spread (ΔS), term spread ($TERM$), change in ten-year T-bond yield (ΔTB), dividend yield (DIV), excess market return (RET), inflation (INF), market liquidity ($ILLIQ$), and the natural log of aggregate systematic variation, $\ln ASV$. As a robustness check, we replace $\ln AIV$ by $\ln \psi_t$ in [8] and [9] but exclude $\ln ASV$ on the right-hand side. The Akaike Information Criteria (AIC) determines the number of lags in each regression.[5] Granger causality tests using idiosyncratic to systematic variation ratios are identical, except $\ln ASV$ is omitted.

Table V summarizes these tests. Each column is a regression as in [8] or [9]. Each row gives, for each predictor variable, a joint-χ^2 test statistic and, in parenthesis, p-value, for rejecting zero coefficients on all that variable's lags. For brevity, the table only reported the results using the baseline definition of stock return idiosyncrasy. Alternative definitions yield consistent results. Stock returns idiosyncrasy Granger causes ($p < 0.01$) both measures of economic growth; but neither economic growth measures Granger causes returns idiosyncrasy. The significance of stock return idiosyncrasy exceeds that of all other leading indicators (controls) Granger causing GDP growth and exceeds all except systematic return variation in Granger causing industrial production growth. Thus, stock returns idiosyncrasy Granger causes economic growth and reverse causality is rejected.

3.6 Forecasting Economic Growth Out-of-Sample

The above shows idiosyncrasy consistently predicting economic growth "in-sample", that is, using all available data. "Out-of-sample" tests are more robust to selection bias and over-fitting (Fair and Shiller, 1990; Estrella and Mishkin, 1998). This section uses recursive in-sample regression estimates to provide out-of-sample forecasts of real GDP and industrial production

[5] Using BIC instead of AIC to select the lag orders does not materially change the results.

growth up to four quarters following the in-sample estimation window. Stock returns idiosyncrasy is shown to have significant out-of-sample forecasting power.

The unrestricted in-sample regression is

$$\Delta \ln Y_{t+h} = \alpha + \sum_{k=0}^{n} \beta_{t-k} \ln AIV_{t-k} + \sum_{k=0}^{n} \gamma_{t-k} X_{t-k} + \sum_{k=0}^{n} \delta_{t-k} \Delta \ln Y_{t-k} + \sum_{k=0}^{n} \beta'_{t-k} \ln ASV_{t-k} + \varepsilon_{t+h}, \quad [10]$$

where $\Delta \ln Y_{t+h}$ is growth in either GDP or industrial production in quarter $t + h$, h = 1, 2, 3, or 4; X is the vector of control variables from section 2.2, used here in the in-sample estimation, and k denotes the number of lags included in the forecasting model, determined by AIC. The restricted model is the unrestricted model but with the coefficients of all lags of idiosyncrasy set to zero – that is, $\beta_t = \ldots = \beta_{t-k} = 0$. We also run regression [10] using $\sum_{k=0}^{n} \beta_{t-k} \ln \psi_{t-k}$ instead of $\sum_{k=0}^{n} \beta_{t-k} \ln AIV_{t-k} + \sum_{k=0}^{n} \beta'_{t-k} \ln ASV_{t-k}$.

Regression [10] is estimated recursively, starting with a 100-quarter window from 1947Q1 through 1971Q4. The estimation window then expands one quarter as the forecasting point moves one quarter forward. Increased out-of-sample forecasting power from including stock returns idiosyncrasy is assessed with *MSE-F* and *ENC-NEW* tests.

The *MSE-F* test tests whether the unrestricted regression has lower out-of-sample forecasting mean squared error (*MSE*) than the restricted model (McCracken, 2007).

$$MSE\text{-}F \equiv (p - h + 1) \frac{MSE_r - MSE_u}{MSE_u}, \quad [11]$$

where p is the number of out-of-sample forecasts and h is the forecast horizon. The subscripts r and u denote the restricted and unrestricted predictive models, respectively. A significant one-tailed *MSE-F* statistic indicates better forecasting accuracy in the unrestricted than restricted model.

The *ENC-NEW* statistic tests if forecasts of the restricted model "encompass" forecasts

made of the unrestricted model. Clark and McCracken (2001) show this test has higher power than the *MSE-F* test and define

$$ENC\text{-}NEW = (p - h + 1)\frac{\sum_{t+h}(\epsilon_{r,t+h}^2 - \epsilon_{r,t+h}\epsilon_{u,t+h})}{\sum_{t+h}\epsilon_{u,t+h}^2} \quad [12]$$

Where ϵ_r and ϵ_u denote forecast errors from the restricted and unrestricted model, respectively. A significant *ENC-NEW* statistic indicates better forecasting accuracy from the unrestricted than restricted model.

Table VI reports the *MSE-F* and *ENC-NEW* test statistics using the baseline *AIV* definition, with forecast horizons from one to four quarters out. Defining *AIV* with the four-factor model or the Campbell et al model generates consistent results. In the one-quarter ahead forecasts (*h=1*), both idiosyncrasy measures significantly improve the accuracy in forecasting the growth rates of real GDP and of industrial production. All *ENC-NEW* and MSE-F test statistics are significant at the 10% level or better.

The forecasting performance of idiosyncrasy remains strong when the forecast horizon is extended to two to three quarters (*h=2 or 3*). Both test statistics are significant at 10% or better for models predicting $\Delta\ln IP_{t+k}$. The MSE-F statistics are also significant for the models predicting $\Delta\ln GDP_{t+2}$ with $\ln AIV_t$ and predicting $\Delta\ln GDP_{t+3}$ with $\ln\psi_t$. As the forecast horizon increases to four quarters (*h=4*) the forecasting performance of idiosyncrasy fades. Thus, stock returns idiosyncrasy significantly improves the performance of models forecasting real GDP growth and industrial production growth up to three quarters ahead.

4. GDP Growth Decomposition

This section explores how higher stock return idiosyncrasy forecasts higher next-quarter GDP by decomposing GDP growth into growth rates of its major components: government spending (G_t),

aggregate consumption (C_t), and investment (I_t).[6] Data are from the Real Gross Domestic Product Table of the Bureau of Economic Analysis. If higher stock returns idiosyncrasy signifies disequilibrating shocks, which induce heterogeneous changes in household- and firm-level incomes, wealth and risk exposure, government spending, aggregate consumption, and/or investment may then change as the economy equilibrates.

4.1 Forecasting Government Spending Growth

Disequilibrating shocks have winners and losers, and government spending increases as the losers activate social safety nets. Thus, Bansal, Croce, Liao and Rosen (2019) relate increased uncertainty to reallocating resources from private to the public sector uses.

Panel B of Table VII shows ln AIV_t attracting insignificant coefficients in predicting higher next-quarter government expenditure growth, $\Delta \ln G_{t+1} = \ln G_{t+1} - \ln G_t$, across all specifications. Idiosyncratic volatility does not appear to forecast expansionary government spending. However, idiosyncrasy significantly predicts next-quarter growth in *GDP* minus *G* in analogs of [4], generating (untabulated) results qualitatively identical to those in Panels A and B of Table III. These tests, presented in Appendix Table A2, show that high stock returns idiosyncrasy helps forecast growth in private sector components of aggregate output.

4.2 Forecasting Consumption Growth

Disequilibrating shocks can affect the expected values and risks of households' future incomes, investment portfolios, and human capital valuations heterogeneously. Consequently, some households raise their consumption, and others cut back. Herskovic, Kelly, Lustig and Van Niewerburgh (2016) associate increased idiosyncratic stock return risk with increased dispersion in household-level consumption growth.

[6] We thank an anonymous referee for suggesting this exercise.

This increased heterogeneity could alter aggregate consumption growth, which we define as the difference in logs of aggregate personal consumption expenditures: $\Delta \ln C_{t+1} = \ln C_{t+1} - \ln C_t$. Panel A of Table VII shows higher idiosyncratic stock return variation (ln *AIV*) predicting higher next-quarter consumption growth ($p \leq 0.01$). The results are robust to alternative idiosyncratic variation definitions.

This finding accords with most disequilibrating shocks in the period we examine enhancing productivity. Increased heterogeneity predicting higher aggregate consumption may reflect Agarwal and Qian's (2014) finding that positive shocks increase household consumption immediately juxtaposed with Ganong and Noel's (2019) finding that negatively shocked households delay reducing their consumption.[7]

4.3 Forecasting Investment Growth

We posit that disequilibration changes forward-looking equity prices idiosyncratically to reflect new information about firms' prospects. If firms with improved prospects increased their investment and firms with diminished prospects delayed disinvesting, the next-quarter aggregate investment might rise. However, Panel C of Table VII shows that higher aggregate idiosyncratic variation, ln AIV_t, though it attracts positive coefficients, does not significantly forecast next-quarter gross private-sector domestic investment growth. Idiosyncratic relative to systematic variation, ln ψ_t, does attract positive significant coefficients; however, this reflects ln ASV_t attracting negative significant coefficients.

While disequilibration alters firms' investment options, several considerations may delay actual investments and prevent increased aggregate investment in the near term. First, real option

[7] Agarwal and Qian (2014) show positively shocked households raise their consumption in anticipation of increased income using credit. Ganong and Noel (2019) show negatively shocked households receiving unemployment benefit checks do not reduce their consumption until the unemployment insurance expires, suggesting present-bias or myopia in responding to expected income losses.

considerations govern the timing of investments. Growth option values rise with risk (Brennan and Schwarz 1985) and self-interested managers delay downsizing (Myers and Lambrechtt 2022), aggregate investment, like consumption, might rise. However, because investment timing depends on idiosyncratic risk nonlinearly (Liu and Wang 2021) and on other interacting considerations (e.g., Miao and Wang 2007; Leippold and Stromberg 2017), real options value optimization can readily cause firms to delay investments (Guthrie 2009, Chs. 7, 8 and 9). Consequently, a disequilibrating shock that altered different firms' growth options idiosyncratically, causing immediate idiosyncratic movements in forward-looking stock prices, but might not boost next-quarter aggregate investment.[8]

Bachmann and Bayer (2014) report a strong pro-cyclicality in the cross-sectional dispersion of firm-level investment rates. We also find investment rate dispersion positively correlated with stock return idiosyncratic variation ($\rho = 0.21$, p-value $=0.02$).[9] We, therefore, explore whether or not dispersion in investment rates predicts next-quarter investment growth. We successfully replicate Bachmann and Bayer's (2014) finding that investment dispersion is contemporaneously positively correlated with output growth controlling for the economic indicators in equation [4]. However, regressions analogous to Table III and Table VII Panel C using investment dispersion instead of *AIV* leave the former insignificant in predicting GDP growth and marginally significant in predicting industrial production growth. Moreover,

[8] Our findings complement Chang et al. (2021), who link higher firm-level idiosyncratic volatility to higher investment real option values given leverage and credit risk with shareholders having limited liability. Higher firm-level dispersion along such lines might reflect disequilibration and subsequent equilibration. Chang et al. find that the response of firm-level investment to idiosyncratic volatility varies across firms, positive for firms with low credit risk and negative for firms with high credit risk, consistent with the overall non-predictivity of idiosyncratic volatility to aggregate investment we find.

[9] We define quarterly investment rate as quarterly net capital expenditure over quarter-beginning net property, plant, and equipment for CRSP/Compustat merged firms from 1984Q1 to 2020Q4. Investment dispersion is the cross-sectional variance of firm-level investment rate.

including investment dispersion as an additional explanatory variable in these same regressions also attracts insignificant or marginally significant coefficients, but leaves the coefficients of *AIV* largely unchanged. This is consistent with the forward-looking nature of stock returns (Black 1981) and with elevated AIV delaying the optimal exercise of investment options (Liu and Wang 2021). Appendix Tables A3 summarizes these results.[10]

4.4 Forecasting Innovation and Productivity Growth

If most disequilibrium shocks reflect new productivity-increasing technologies, higher stock return idiosyncrasy might most strongly predict increased next-quarter investment in innovation and productivity improvement, rather than in the investment measures in Panel C of Table VII.

Panels A of Table VIII indeed show higher stock returns idiosyncrasy predicting increased next-quarter innovation intensity, measured as quarterly growth (log differences) in simple, $\Delta \ln PAT_t$, or citation-weighted, $\Delta \ln CIT_t$, patent counts aggregated across U.S. listed firms from 1947Q1 to 2016Q4, as in Kogan et al. (2017).[11] Higher stock returns idiosyncrasy, measured as either aggregate, $\ln AIV_t$, or relative, $\ln \psi_t$, stock return idiosyncrasy, significantly predicts increases in next-quarter citation-weighted patent intensity; relative idiosyncrasy also significantly predicts increased simple patent counts.

Panel B of Table VIII shows that elevated stock returns idiosyncrasy, $\ln AIV$, predicts next-quarter growth in business sector total factor productivity (ΔTFP) and labor productivity (ΔLP)

[10] In untabulated tests, we find dispersion in TFP growth, based on Imrohoroglu and Tuzel,'s (2014) online data, to contemporaneously correlate most closely with ASV and, like ln ASV, attracts a negative coefficient when included as an additional control variable in the Table III regressions.

[11] Downloadable from Noah Stoffman's website: https://host.kelley.iu.edu/nstoffma/.The patent data are available up 2019Q3 but appear to be incomplete after 2016. Both patent count and citations decline sharply after 2016. Including data from 2017Q1 to 2019Q3 does not materially change the results.

over 1947Q1 to 2020Q4.[12] The idiosyncrasy ratio, however, fails to attain significance. Note that ln AIV_t predicts subsequent quarter productivity growth above and beyond predictability by leading indicators used in prior studies. Higher dividend yield (*DIV*), higher market excess return (*RET*), and lower inflation (*INF*) also predict higher next-quarter productivity growth.

5. Conclusions

Our findings support stock return idiosyncrasy being added to the roster of leading indicators forecasters can use to predict macroeconomic variables in the near-term future. More specifically, stock returns idiosyncrasy defensibly proxies stock markets capitalizing new information for disequilibrating shocks, which subsequently affect firms and households heterogeneously in ways that increase next quarter investment in innovation, productivity growth, aggregate consumption growth, and output growth. Stock return idiosyncrasy is readily calculable from standard databases, and so can readily be exploited by central banks, government agencies, and others required to provide near-term macro forecasts.

Moreover, stock returns idiosyncrasy Granger causes growth in real GDP and industrial production, none of which Granger causes stock return idiosyncrasy. Out-of-sample tests show stock return idiosyncrasy significantly improving the forecasting accuracy of simple models predicting output growth one to three quarters ahead.

Our results build upon important prior results in several ways. First, prior work shows firm-level heterogeneity in e.g., investment rates (Bachman and Bayer 2014) to be contemporaneously pro-cyclical. Our findings go a step further by showing idiosyncrasy in stock returns to be a new leading indicator in that it economically and statistically significantly

[12] The data, created by John Fernald, can be downloaded from San Francisco Federal Reserve website: https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/.

forecasts next-quarter macroeconomic growth both in and out-of-sample. This applies Black's (1981) insight that stock returns are forward-looking, anticipating corporate actions, whereas output, investment and productivity contemporaneously reflect actual corporate actions. While contemporaneous correlations are very important to economists, leading indicators are important to governments, central banks and portfolio managers charged with forecasting the future. Stock return idiosyncrasy appears to be a new leading indicator at least as useful as those currently in use.

Second, prior studies have examined stock return dispersion (cross-sectional variation), whereas we find idiosyncrasy to be of unique interest as a new leading indicator. Stiver (2003) find a positive relation between return dispersion and future market volatility, suggesting return dispersion containing useful information about the future economic state. Garcia et al. (2013) correctly note that cross-section returns variance and stock returns idiosyncrasy are highly correlated. This arises mechanically, and spelling this out shows that their correlation is imperfect and that this imperfection is economically interesting. Mechanically, cross-sectional variation in stock returns is closely correlated with both the systematic, *ASV*, and idiosyncratic, *AIV*, stock return variation. Its first component reflects individual firms' stocks moving in harmony with the market, and is thus a measure akin to the variance of market indexes or imputed estimates thereof such as the VIX. Consistent with prior work, e.g., Alfaro, Bloom, and Lin (2018), we find increased systematic stock return variation to forecast reduced output growth and its sub-components like consumption and investment. Our results show idiosyncratic variation, in stark contrast, to forecast increased next-quarter macroeconomic growth. These findings suggest that distinguishing idiosyncratic from systematic returns variation is useful because they convey very different information.

Third, much prior theoretical and empirical work links stock returns to the real economy in equilibrium (e.g., Cochrane 1991; Liu, Whited and Zhang 2009). Our results instead explicitly follow Black's (1981) suggestion that economically significant disequilibria intermittently arise and that stock returns might usefully forecast the subsequent equilibration process and its macroeconomic implications. Black associates disequilibration with misallocated resources, such as arise from incomplete information, contracting problems, agency problems, and the like; whereas Schumpeter (1911) associates disequilibration with adaptation to improved circumstances, such as arise from productivity-enhancing innovations. Our findings support Schumpeter's view of disequilibrium as most often being associated with productivity-increasing and equilibration as elevating productivity and growth. This is consistent with a series of new technologies causing disequilibria (Schumpeter 1911) and subsequent equilibration as those new technologies come into use fueling economic growth (Solow 1957).

Fourth, our results add to prior work distinguishing "good" and 'bad" volatility Bekaert and Engstrom (2017) associated with positive and negative innovations (Segal et al. 2015). Stein and Stone (2013) find currency and commodity price shocks to cut investment and thus constitute "bad" volatility. This dichotomy parallels that between heightened idiosyncratic stock return variation reflecting Black's (1981) "bad" disequilibrium and Schumpeter's (1911) "good" disequilibrium. Our findings are consistent with Black's (1981) thesis that higher idiosyncratic stock return variation reflects an economy thrown into disequilibrium, but with Schumpeter's (1911) thesis that disequilibria are most often due to technological change and thus responsible for productivity growth (Solow 1957).

Appendix A. Variable Definitions and Data Sources

Variable	Definition	Source
AIV_t	*Aggregate idiosyncratic variation* AIV_t in quarter *t* is the value-weighted cross-section mean across all NYSE, Nasdaq, and Amex-listed common stocks *j* (share code 10 or 11) that quarter of $SSE_{j,t}$, the sum of squared residual variation in the time-series regression $R_{j,s} = \alpha_{j,t} + \beta_{j,t} R_{m,s} + \varepsilon_{j,s}$, where $R_{j,s}$ and $R_{m,s}$ are total returns of stock *j* and the market, respectively, on day *s* in quarter *t*.	CRSP[13]
ASV_t	*Aggregate systematic variation* ASM_t in quarter *t* is the value-weighted cross-section mean across all NYSE, Nasdaq, and Amex-listed common stocks *j* (share code 10 and 11) that quarter of $SSM_{j,t}$, the sum of squared explained variation in stock-level time-series regressions used to obtain $SSE_{j,t}$.	CRSP
ψ_t	*Relative idiosyncrasy* ψ_t in quarter *t* is AIV_t / ASV_t.	CRSP
$\Delta \ln GDP_t$	GDP growth is log difference in seasonally adjusted real GDP between quarter *t* and *t-1*.	BEA[14]
$\Delta \ln IP_t$	Industrial production growth is log difference in seasonally adjusted industrial production index between quarter *t* and *t-1*. Quarterly industrial production is mean monthly industrial production within a quarter.	FRED[15]
$\Delta \ln C_t$	Consumption growth is the log difference in real personal consumption expenditures between quarter *t* and *t-1*.	BEA
$\Delta \ln G_t$	Government spending growth is the log difference in real government spending between quarter *t* and *t-1*.	BEA
$\Delta \ln I_t$	Investment growth is the log difference in private non-residential fixed investment between quarter *t* and *t-1*.	BEA
ΔS_t	*Change in credit spread*, Baa rated bond yields minus ten-year government bond yields, from quarter *t-1* to *t*. Quarterly rates are average of respectively monthly rates within each quarter.	FRED
$TERM_t$	*Term premium* is 10-year T-bond yield minus the three-month T-bill rate	FRED
ΔTB_t	*Change in T-bond yield* is the difference from quarter *t-1* to *t* in mean monthly 10-year T-bond yields within each quarter.	FRED
DIV_t	*Dividend yield* is the cumulative dividend yield for the CRSP value-weighted stock portfolio in quarter *t*	CRSP
RET_t	*Excess market return*, cumulative quarterly return of the value-weighted CRSP market index minus the 3-month T-bill rate.	CRSP
INF_t	*Inflation* is the quarterly change in Consumer Price Index (CPI) ending in months in quarter *t*	WRDS

[13] Center for Research in Securities Prices, University of Chicago
[14] Bureau of Economic Analysis
[15] Federal Reserve Bank of St. Louis Economic Data

$ILLIQ_t$	*Illiquidity* is the equal-weighted mean across stocks of daily average absolute return over dollar volume calculated for each NYSE stock.	CRSP
$4F\text{-}AIV_t$	*4F-AIV* for stock *j* in quarter *t* is the residual sum of squares from Carhart's four-factor model $R_{j,s} = \alpha_{j,t} + \beta_{MKT,j,t} R_{m,s} + \beta_{SMB,j,t} SMB_{i,s} + + \beta_{HML,j,t} HML_{i,s} + + \beta_{UMD,j,t} UMD_{i,s} + \varepsilon_{j,s}$. Market-wide *4F-AIV* in quarter *t* is the value-weighted average *AIV* across all common stocks.	CRSP; Kenneth French's website
$4F\text{-}ASV_t$	*4F-ASV* for stock *j* in quarter *t* is the model sum of squares from regression above used to define $4F\text{-}AIV_{j,t}$. Market-wide *4F-ASV* in quarter *t* is the value-weighted average *ASV* across all common stocks.	CRSP; Ken French's website
$C\text{-}AIV_t$	*C-AIV* for stock *j* in quarter *t* is return variation of stock *j* relative to its industry *i*, $\sum_{s\in t}\left(R_{j,i,s} - R_{i,s}\right)^2$. Market-wide *C-AIV* in quarter *t* is the value-weighted average across all common stocks in the quarter. The definition of *C-AIV*, *C-APV*, and *C-ASV* follows Campbell *et al.* (2001) stock return decomposition.	CRSP
$C\text{-}APV_t$	*C-APV* for industry *i* in quarter *t* is return variation of industry *j* relative to the market return, $\sum_{s\in t}\left(R_{i,s} - R_{m,s}\right)^2$. Market-wide *C-APV* in quarter *t* is the value-weighted average across all industries in the quarter.	CRSP
$C\text{-}ASV_t$	*C-ASV* in quarter *t* is the variation of daily market-index return over quarter *t*, $\sum_{s\in t}\left(R_{m,s} - \bar{R}_{m,t}\right)^2$	CRSP
$CFNAI_t$	Quarterly average of monthly values of the Chicago Fed National Activity Index (*CFNAI*), an economic activity index based on 85 economic activity series.	Chicago Fed
$\Delta \ln PAT_t$	Log difference between the number of patent applications between quarter *t* and *t-1*, aggregated across all firms.	Noah Stoffman's website
$\Delta \ln CIT_t$	Log difference between the number of forward-looking citations received by the applied patents between quarter *t* and *t-1*, aggregated across all firms.	
ΔTFP_t	Business sector total factor productivity growth, i.e., the change of output growth less the contribution of capital and labor from quarter *t-1* to *t*.	San Francisco Fed
ΔLP_t	Business sector labor productivity growth in quarter *t*	

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Table I. Summary Statistics

This table lists summary statistics of aggregate idiosyncratic variation (AIV_t), aggregate systematic variation (ASV_t), idiosyncrasy ratio ($\psi_t = AIV_t/ASV_t$), the economic conditions indicators, the growth rate of GDP and industrial production (IP.), and the control variables from 1947Q1 to 2020Q4. Both AIV_t and ASV_t are multiplied by 1,000. See Appendix A for detailed definitions.

Variable	*Obs*	*Mean*	*Std. Dev.*	*P5*	*P50*	*P95*
$AIV_{t\ (\times 10^3)}$	295	0.260	0.196	0.101	0.202	0.606
$ASV_{t\ (\times 10^3)}$	295	0.101	0.131	0.021	0.063	0.321
ψ_t	295	3.887	2.562	1.246	3.271	8.286
$\Delta lnGDP_{t+1}$	295	0.008	0.012	-0.009	0.008	0.023
$\Delta lnIP_{t+1}$	295	0.007	0.022	-0.029	0.007	0.039
ΔS_t	295	0.005	0.301	-0.393	-0.010	0.423
$TERM_t$	295	1.427	1.095	-0.263	1.303	3.353
ΔTB_t	295	-0.005	0.428	-0.703	0.017	0.577
DIV_t	295	0.008	0.004	0.004	0.008	0.015
RET_t	295	-0.009	0.085	-0.170	0.002	0.116
INF_t	295	0.008	0.010	-0.005	0.007	0.026
$ILLIQ_t$	295	-0.015	0.245	-0.430	-0.020	0.412

Table II. Correlation Matrix

This table reports the Pearson correlation coefficients between the variables used in the analysis over 295 quarters from 1947Q1 to 2020Q4. P-values are reported in parentheses. Boldface denotes significance the 10% level or better. See Appendix A for variable definitions.

	$\ln AIV_t$	$\ln ASV_t$	$\ln \psi_t$	$\Delta \ln GDP_{t+1}$	$\Delta \ln IP_{t+1}$	ΔS_t	$TERM_t$	ΔTB_t	DIV_t	RET_t	INF_t
$\ln ASV_t$	**0.706** **(0.00)**										
$\ln \psi_t$	-0.071 (0.23)	**-0.756** **(0.00)**									
$\Delta \ln GDP_{t+1}$	**-0.160** **(0.01)**	**-0.301** **(0.00)**	**0.276** **(0.00)**								
$\Delta \ln IP_{t+1}$	**-0.226** **(0.00)**	**-0.362** **(0.00)**	**0.302** **(0.00)**	**0.837** **(0.00)**							
ΔS_t	**0.222** **(0.00)**	**0.287** **(0.00)**	**-0.199** **(0.00)**	**-0.252** **(0.00)**	**-0.373** **(0.00)**						
$TERM_t$	0.080 (0.17)	0.075 (0.20)	-0.032 (0.59)	**0.130** **(0.03)**	**0.116** **(0.05)**	**-0.150** **(0.01)**					
ΔTB_t	**-0.109** **(0.06)**	**-0.133** **(0.02)**	0.087 (0.13)	0.053 (0.36)	**0.119** **(0.04)**	**-0.531** **(0.00)**	**-0.173** **(0.00)**				
DIV_t	**-0.438** **(0.00)**	**-0.281** **(0.00)**	-0.009 (0.88)	0.087 (0.13)	0.032 (0.58)	0.061 (0.30)	**-0.112** **(0.05)**	**0.008** **(0.90)**			
RET_t	**-0.286** **(0.00)**	**-0.341** **(0.00)**	**0.217** **(0.00)**	**0.308** **(0.00)**	**0.319** **(0.00)**	**-0.156** **(0.01)**	**0.192** **(0.00)**	**-0.196** **(0.00)**	0.038 (0.52)		
INF_t	0.091 (0.12)	0.039 (0.50)	0.029 (0.62)	-0.056 (0.34)	-0.053 (0.36)	**-0.144** **(0.01)**	**-0.243** **(0.00)**	**0.287** **(0.00)**	**0.216** **(0.00)**	**-0.253** **(0.00)**	
$ILLIQ_t$	**0.118** **(0.04)**	**0.310** **(0.00)**	**-0.328** **(0.00)**	**-0.251** **(0.00)**	**-0.253** **(0.00)**	**0.189** **(0.00)**	**-0.122** **(0.04)**	**0.169** **(0.00)**	-0.081 (0.17)	**-0.510** **(0.00)**	-0.016 (0.78)

Table III. Predicting Economic Growth with Stock Returns Idiosyncrasy

This table predicts next quarter economic growth with current quarter stock returns idiosyncrasy over 294 quarters from 1947Q1 to 2020Q4. Panel A reports regressions using quarter *t* aggregate idiosyncratic stock return variation, $\ln AIV_t$, to peredict quarter $t+1$ GDP growth, $\Delta \ln GDP_{t+1}$, or industrial production growth, $\Delta \ln IP_{t+1}$. Regressions 3A.1 and 3A.2 use our baseline decomposition of [1] into [2] and [3] to define idiosyncratic, AIV_t, and systematic, ASV_t components; 3A.3 and 3A.4 use Carhart's (1997) 4-factor model [6]; 3A.5 and 3A.6 use Campbell et al. (2001) decomposition [7]. Control variables, defined in Appendix A, are: change in credit spread (*⊿S*), term spread (*TERM*), change in the ten-year T-bond yields(*⊿TB*), dividend yield (*DIV*), inflation (*INF*), market premium (*RET*), stock market liquidity (*ILLIQ*). Panel A regressions also control for systematic risk ($\ln ASV_t$). Regressions 3A.5 and 3A.6 using the Campbell et al. (2001) decomposition also control for primary industry-related risk ($\ln APV_t$). Panel B repeats the exercise, replacing $\ln SSE_t$ and $\ln SSM_t$ in each Panel A specification with their ratio $\ln \psi_t = \ln AIV_t - \ln ASV_t$ The denominator is systematic plus industry risk in 3B.5 and 3B.6 using Campbell et al. (2001) decomposition. Newey-West p-values are in parentheses. Boldface denotes significance at 10% of better.

Panel A. Idiosyncratic Return Variation Predicting Next Quarter Economic Growth

$\Delta \ln Y_{t+1}$ =	$\Delta \ln GDP_{t+1}$	$\Delta \ln IP_{t+1}$	$\Delta \ln GDP_{t+1}$	$\Delta \ln IP_{t+1}$	$\Delta \ln GDP_{t+1}$	$\Delta \ln IP_{t+1}$
Decomposition	*Baseline definition*		*Carhart (1997) 4-factor*		*Campbell et al (2001)*	
Regression	3A.1	3A.2	3A.3	3A.4	3A.5	3A.6
$\ln AIV_t$	**0.332**	**0.376**	**0.411**	**0.590**	**0.366**	**0.675**
	(0.04)	**(0.06)**	**(0.02)**	**(0.02)**	**(0.09)**	**(0.10)**
ΔS_t	**-0.007**	**-0.015**	**-0.007**	**-0.015**	**-0.006**	**-0.015**
	(0.02)	**(0.01)**	**(0.02)**	**(0.01)**	**(0.03)**	**(0.01)**
$TERM_t$	0.001	0.001	0.001	0.001	0.001	0.000
	(0.14)	(0.17)	(0.17)	(0.20)	(0.21)	(0.45)
ΔTB_t	0.000	-0.001	0.000	-0.001	0.001	-0.000
	(0.85)	(0.80)	(0.81)	(0.81)	(0.71)	(0.95)
DIV_t	0.243	0.088	0.177	0.003	0.216	-0.073
	(0.19)	(0.71)	(0.39)	(0.99)	(0.34)	(0.81)
RET_t	0.024	**0.052**	0.025	**0.053**	**0.027**	**0.059**
	(0.11)	**(0.03)**	(0.12)	**(0.03)**	**(0.10)**	**(0.03)**
INF_t	-0.046	-0.040	-0.058	-0.062	-0.067	-0.101
	(0.44)	(0.66)	(0.34)	(0.49)	(0.30)	(0.32)
$ILLIQ_t$	-0.002	-0.002	-0.002	-0.002	-0.003	-0.003
	(0.31)	(0.70)	(0.28)	(0.74)	(0.24)	(0.58)
$\ln ASV_t$	**-0.378**	**-0.581**	**-0.450**	**-0.772**	**-0.308**	**-0.328**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.02)**	**(0.03)**
$\ln SSI_t$					-0.109	-0.567
					(0.62)	(0.24)
$\Delta \ln Y_t$	-0.019	**0.246**	-0.020	0.242	-0.020	0.237
	(0.91)	**(0.10)**	(0.91)	(0.11)	(0.91)	(0.13)
Adj. R^2	0.155	0.276	0.156	0.281	0.155	0.278

Panel B. Relative Idiosyncratic Variation Predicting Next Quarter Growth

$\Delta \ln Y_{t+1}$ =	$\Delta \ln GDP_{t+1}$	$\Delta \ln IP_{t+1}$	$\Delta \ln GDP_{t+1}$	$\Delta \ln IP_{t+1}$	$\Delta \ln GDP_{t+1}$	$\Delta \ln IP_{t+1}$
Decomposition	*Baseline definition*		*Carhart (1997) 4-factor*		*Campbell et al (2001)*	
Regression	3B.1	3B.2	3B.3	3B.4	3B.5	3B.6
$\ln \psi_t$	**0.378**	**0.577**	**0.449**	**0.766**	**0.483**	**0.762**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.01)**	**(0.00)**
ΔS_t	**-0.007**	**-0.016**	**-0.007**	**-0.016**	**-0.007**	**-0.015**
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.02)**	**(0.01)**
$TERM_t$	0.001	0.001	0.001	0.001	0.001	0.000
	(0.15)	(0.27)	(0.19)	(0.31)	(0.25)	(0.46)
ΔTB_t	0.000	-0.001	0.001	-0.001	0.001	-0.000
	(0.85)	(0.81)	(0.80)	(0.82)	(0.70)	(0.92)
DIV_t	0.274	0.224	0.198	0.102	0.210	0.124
	(0.16)	(0.24)	(0.36)	(0.60)	(0.27)	(0.51)
RET_t	**0.025**	**0.055**	**0.026**	**0.055**	**0.028**	**0.059**
	(0.10)	**(0.02)**	**(0.10)**	**(0.02)**	**(0.08)**	**(0.01)**
INF_t	-0.050	-0.061	-0.063	-0.083	-0.085	-0.117
	(0.40)	(0.51)	(0.29)	(0.37)	(0.16)	(0.23)
$ILLIQ_t$	-0.002	-0.002	-0.002	-0.001	-0.003	-0.002
	(0.32)	(0.76)	(0.29)	(0.79)	(0.22)	(0.71)
$\Delta \ln Y_t$	-0.017	0.253	-0.018	0.247	-0.020	0.247
	(0.92)	(0.10)	(0.91)	(0.11)	(0.91)	(0.11)
Adj. R^2	0.158	0.277	0.158	0.282	0.164	0.282

Table IV. Stock Returns Idiosyncrasy Predicting Alternative Economic Growth Measures

This table reports regressions using stock returns idiosyncrasy to predict alternative measures of improving economic conditions. Stock returns idiosyncrasy is either $\ln AIV_t$ or $\ln \psi_t$, and alternative economic growth measures are quarterly averages of the Chicago Federal Reserve's monthly National Activity Index (*CFNAI*). These data are available from 1967Q2 to 2020Q4. Regressions 4.1 and 4.2 use our baseline decomposition of [1] into [2] and [3] to define aggregate idiosyncratic, AIV_t, and systematic, ASV_t variation in stock returns; 4.3 and 4.4 use Carhart's (1997) 4-factor model [6]; 4.5 and 4.6 use Campbell et al. (2001) decomposition [7], which also generates a primary-industry-level stock return variation $\ln SPV_t$. Control variables are: change in credit spread (ΔS), term spread (*TERM*), change in ten-year Treasury bond yields (ΔTB), Dividend yield (*DIV*), inflation (*INF*), excess market return (*RET*), stock market liquidity (*ILLIQ*) and, in even-numbered specifications, systematic stock return variation ($\ln ASV_t$). Newey-West adjusted p-values are in parentheses. Boldface denotes a significance level of 10% or better. Variable definitions are in Appendix A.

$\Delta \ln Y_{t+1}$ =	$CFNAI_{t+1}$					
Decomposition	*Baseline definition*		*Carhart (1997) 4-factor*		*Campbell et al (2001)*	
Regression	6.1	6.2	6.3	6.4	6.5	6.6
$\ln AIV_t$	**0.084**		**0.125**		0.143	
	(0.05)		**(0.01)**		(0.12)	
$\ln \psi_t$		**0.090**		**0.135**		**0.127**
		(0.06)		**(0.04)**		**(0.05)**
ΔS_t	-0.138	-0.139	-0.144	-0.146	-0.141	-0.139
	(0.19)	(0.21)	(0.18)	(0.19)	(0.17)	(0.20)
$TERM_t$	**0.049**	**0.049**	**0.046**	**0.046**	**0.044**	**0.046**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.03)**	**(0.02)**
ΔTB_t	**-0.224**	**-0.224**	**-0.221**	**-0.221**	**-0.212**	**-0.215**
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.02)**	**(0.01)**
DIV_t	11.440	11.746	8.254	8.660	3.812	7.455
	(0.24)	(0.24)	(0.38)	(0.35)	(0.76)	(0.43)
RET_t	**2.117**	**2.129**	**2.095**	**2.115**	**2.182**	**2.155**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
INF_t	**4.031**	**4.049**	**3.417**	**3.429**	3.336	3.356
	(0.06)	**(0.05)**	**(0.10)**	**(0.10)**	(0.11)	(0.11)
$ILLIQ_t$	**0.248**	**0.249**	**0.254**	**0.255**	0.226	**0.242**
	(0.10)	**(0.10)**	**(0.08)**	**(0.09)**	(0.13)	**(0.10)**
$\ln ASV_t$	**-0.091**		**-0.137**		-0.051	
	(0.08)		**(0.05)**		(0.30)	
$\ln APV_t$					-0.106	
					(0.31)	
ΔY_t	**0.587**	**0.590**	**0.572**	**0.576**	**0.564**	**0.573**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
Adj. R^2	0.521	0.523	0.525	0.528	0.521	0.526

Table V. Economic Growth and Stock Returns Idiosyncrasy–Granger Causality Tests

This table reports Granger causality tests between stock returns idiosyncrasy and economic growth. Vector autoregressions 5.1 and 5.2 test for stock returns idiosyncrasy Granger causing economic growth. Joint-χ^2 statistics and p-values are reported for *k* lags of the predicted variable, stock returns idiosyncrasy, and each control variable. Autoregressions 5.3 and 5.4 test for economic growth Granger causing stock returns idiosyncrasy, again reporting joint-χ^2 statistics and p-values for each variable's set of lags. Control variables are as in Table III: change in credit spread (ΔS), term spread (*TERM*), change in the ten-year T-bond yields(ΔTB), dividend yield (*DIV*), inflation (*INF*), market premium (*RET*), and stock market liquidity (*ILLIQ*). The number of lags *k* is determined by AIC. Boldface denotes significance at 10% or better. Variable definitions are in Appendix A.

	Granger Causing Economic Growth				***Granger Causing Stock Returns Idiosyncrasy***			
	$\Delta \ln GDP_t$		$\Delta \ln IP_t$		$\ln AIV_t$		$\ln \psi_t$	
Predictor	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8
$\Delta \ln GDP_{t-k \text{ to } t-1}$	7.83 (0.16)	7.28 (0.20)			5.30 (0.38)		3.61 (0.61)	
$\Delta \ln IP_{t-k \text{ to } t-1}$			**22.00** **(0.00)**	**18.37** **(0.00)**		6.16 (0.29)		4.99 (0.42)
$\ln AIV_{t-k \text{ to } t-1}$	**17.80** **(0.00)**		**18.24** **(0.00)**		**529.84** **(0.00)**	**539.76** **(0.00)**		
$\ln \psi_{t-k \text{ to } t-1}$		**14.87** **(0.01)**		**18.82** **(0.00)**			**106.21** **(0.00)**	**102.27** **(0.00)**
$\Delta S_{t-k \text{ to } t-1}$	4.90 (0.43)	4.69 (0.45)	7.69 (0.17)	7.25 (0.20)	5.54 (0.35)	4.22 (0.52)	0.98 (0.96)	1.19 (0.95)
$TERM_{t-k \text{ to } t-1}$	8.35 (0.14)	8.48 (0.13)	6.28 (0.28)	5.38 (0.37)	**11.52** **(0.04)**	**12.12** **(0.03)**	5.03 (0.41)	4.59 (0.47)
$\Delta TB_{t-k \text{ to } t-1}$	7.03 (0.22)	5.54 (0.35)	9.09 (0.11)	7.51 (0.19)	**14.43** **(0.01)**	**15.38** **(0.01)**	0.41 (1.00)	0.79 (0.98)
$DIV_{t-k \text{ to } t-1}$	**22.41** **(0.00)**	**18.77** **(0.00)**	**12.23** **(0.03)**	**12.18** **(0.03)**	**17.85** **(0.00)**	**18.96** **(0.00)**	4.09 (0.54)	4.39 (0.49)
$RET_{t-k \text{ to } t-1}$	**11.78** **(0.04)**	**13.26** **(0.02)**	**15.44** **(0.01)**	**17.12** **(0.00)**	2.72 (0.74)	2.16 (0.83)	7.50 (0.19)	6.64 (0.25)
$INF_{t-k \text{ to } t-1}$	**12.55** **(0.03)**	**9.49** **(0.09)**	**9.63** **(0.09)**	8.51 (0.13)	**30.65** **(0.00)**	**28.49** **(0.00)**	1.82 (0.87)	2.16 (0.83)
$ILLIQ_{t-k \text{ to } t-1}$	**9.15** **(0.10)**	8.08 (0.15)	8.16 (0.15)	8.13 (0.15)	5.93 (0.31)	6.68 (0.25)	1.04 (0.96)	1.10 (0.95)
$ln\ ASV_{t-k \text{ to } t-1}$	**13.59** **(0.02)**		**18.16** **(0.00)**		**21.31** **(0.00)**	**24.78** **(0.00)**		
k =	5	5	5	5	5	5	5	5

Table VI. Forecasting Future Economic Growth with Idiosyncrasy Out-of-Sample

This table reports *MSE-F* (Equation [11]) and *ENC-NEW* (Equation [12]) test statistics to evaluate the performance of idiosyncrasy in out-of-sample forecasts of future economic growth. Both tests compare forecasting accuracy of a restricted model, where lagged economic growth measures and lagged control variables predict future economic growth, to an unrestricted model, where idiosyncrasy is also included as a predictor. Both models are estimated recursively starting with a 100-quarter window from 1947Q1 to 1971Q4. The window expands one quarter at a time as the forecasting point moves one quarter forward. Stock returns idiosyncrasy is defined using the baseline decomposition (equations [1]-[3]), Carhart's (1997) 4-factor model (equation [6]), or Campbell et al. (2001) decomposition (equation [7]). The control variables in the predictive regression are: the change in credit spread (ΔS), term spread (*TERM*), the change in the ten-year Treasury bond yields (ΔTB), Dividend yield (*DIV*), inflation (*INF*), excess market return (*RET*), and stock market liquidity (*ILLIQ*). Systematic return variation (ln *ASV*) is also included as a control variable in regressions using ln *AIV*. The forecast horizon (h) is set to one to four quarters. Critical test values are from Clark and McCracken (2001). Boldface denotes a significance level of 10% of better. Variable definitions are in Appendix A.

$dlnY_{t+h}$ =	Δln GDP_{t+h}		Δln IP_{t+h}		Δln GDP_{t+h}		Δln IP_{t+h}		Δln GDP_{t+h}		Δln IP_{t+h}	
	Baseline definition				*Carhart (1997) 4-factor*				*Campbell et al (2001)*			
	ln AIV_{t-k} *to t-1*	ln ψ_{t-k} *to t-1*	ln AIV_{t-k} *to t-1*	ln $\psi_{t-k\ to\ t-1}$	ln AIV_{t-k} *to t-1*	ln ψ_{t-k} *to t-1*	ln AIV_{t-k} *to t-1*	ln ψ_{t-k} *to t-1*	ln AIV_{t-k} *to t-1*	ln ψ_{t-k} *to t-1*	ln AIV_{t-k} *to t-1*	ln ψ_{t-k} *to t-1*
h=1												
MSE-F	**1.39**	**5.44**	0.45	**6.12**	**1.68**	**5.16**	**1.52**	**6.65**	**1.37**	**6.51**	**2.27**	**7.58**
ENC-NEW	1.32	**5.33**	0.76	**6.51**	**1.94**	**5.70**	**2.03**	**8.79**	0.83	**5.26**	1.37	**7.27**
h=2												
MSE-F	0.41	-0.79	**3.84**	**7.12**	-0.01	-1.56	**4.90**	**8.13**	-1.53	-3.51	0.14	**1.67**
ENC-NEW	0.41	0.29	**3.12**	**6.52**	0.54	0.17	**5.22**	**7.53**	0.04	-0.61	**1.50**	**4.31**
h=3												
MSE-F	**1.17**	**2.39**	**1.80**	**7.86**	**2.88**	**3.07**	**2.37**	**8.07**	**3.08**	**3.07**	**3.50**	**7.42**
ENC-NEW	1.03	**1.62**	**2.08**	**5.82**	**2.16**	**1.98**	**3.33**	**6.22**	**2.15**	**2.28**	**3.40**	**5.80**
h=4												
MSE-F	-1.08	-0.39	-1.36	**5.81**	-1.69	-0.58	**0.44**	**6.99**	-0.71	-0.67	**1.01**	**6.20**
ENC-NEW	-0.16	0.46	-0.21	**4.65**	-0.17	0.38	0.99	**5.58**	0.20	0.41	1.09	**4.93**

Table VII. Stock Returns Idiosyncrasy Predicting the Growth of Government Spending, Consumption, and Private Investment

This table predicts next quarter government spending growth ($\Delta \ln G_{t+1}$), consumption growth ($\Delta \ln C_{t+1}$), and private investment growth ($\Delta \ln I_{t+1}$) with current quarter stock returns idiosyncrasy from 1947Q1 to 2020Q4. Stock returns idiosyncrasy is defined with the baseline decomposition (equations [1]-[3]), Carhart's (1997) 4-factor model (equation [6]), or Campbell et al. (2001) decomposition (equation [7]). Control variables are: change in credit spread (ΔS), term spread (*TERM*), change in ten-year Treasury bond yields (ΔTB), Dividend yield (*DIV*), inflation (*INF*), excess market return (*RET*), stock market liquidity (*ILLIQ*) and, in even-numbered specifications, systematic stock return variation ($\ln ASV_t$). Variable definitions are in Appendix A. Newey-West adjusted p-values are in parentheses. Boldface denotes a significance level of 10% or better.

Panel A. Predicting Growth in Government Spending

$\Delta \ln Y_{t+1}$ =	$\Delta \ln G_{t+1}$					
Decomposition	*Baseline definition*		*Carhart (1997) 4-factor*		*Campbell et al (2001)*	
Regression	7B.1	7B.2	7B.3	7B.4	7B.5	7B.6
$\ln AIV_t$	0.026		-0.045		-0.289	
	(0.86)		(0.81)		(0.21)	
$\ln \psi_t$		-0.079		-0.142		-0.121
		(0.50)		(0.38)		(0.44)
ΔS_t	-0.002	-0.002	-0.002	-0.002	-0.003	-0.002
	(0.47)	(0.54)	(0.46)	(0.53)	(0.43)	(0.52)
$TERM_t$	**-0.001**	-0.001	-0.001	-0.001	-0.000	-0.000
	(0.09)	(0.17)	(0.11)	(0.19)	(0.59)	(0.23)
ΔTB_t	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.59)	(0.57)	(0.60)	(0.58)	(0.43)	(0.53)
DIV_t	**0.663**	**0.593**	**0.667**	**0.614**	**0.862**	**0.609**
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.00)**	**(0.01)**
RET_t	-0.004	-0.006	-0.004	-0.005	-0.010	-0.006
	(0.78)	(0.69)	(0.78)	(0.70)	(0.47)	(0.65)
INF_t	0.043	0.054	0.046	0.058	0.083	0.063
	(0.77)	(0.72)	(0.75)	(0.71)	(0.60)	(0.69)
$ILLIQ_t$	-0.001	-0.002	-0.002	-0.002	-0.000	-0.002
	(0.74)	(0.70)	(0.68)	(0.64)	(0.91)	(0.68)
$\ln ASV_t$	0.079		0.143		-0.150	
	(0.50)		(0.38)		(0.21)	
$\ln APV_t$					**0.575**	
					(0.07)	
$\Delta \ln Y_t$	**0.531**	**0.531**	**0.530**	**0.530**	**0.524**	**0.530**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
Adj. R^2	0.323	0.325	0.324	0.326	0.328	0.325

Panel B. Predicting Consumption Growth

$\Delta \ln Y_{t+1}$ =	$\Delta \ln C_{t+1}$					
Decomposition	*Baseline definition*		*Carhart (1997) 4-factor*		*Campbell et al (2001)*	
Regression	7A.1	7A.2	7A.3	7A.4	7A.5	7A.6
$\ln AIV_t$	**0.492**		**0.636**		**0.714**	
	(0.01)		**(0.00)**		**(0.00)**	
$\ln \psi_t$		**0.458**		**0.578**		**0.640**
		(0.00)		**(0.00)**		**(0.00)**
ΔS_t	**-0.005**	**-0.005**	**-0.005**	**-0.005**	-0.004	-0.004
	(0.08)	**(0.07)**	**(0.09)**	**(0.08)**	(0.12)	(0.11)
$TERM_t$	0.001	0.001	0.000	0.000	0.000	0.000
	(0.40)	(0.40)	(0.47)	(0.45)	(0.71)	(0.57)
ΔTB_t	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001
	(0.60)	(0.59)	(0.64)	(0.63)	(0.84)	(0.77)
DIV_t	0.221	0.199	0.136	0.104	0.073	0.117
	(0.11)	(0.18)	(0.26)	(0.45)	(0.60)	(0.35)
RET_t	0.021	0.020	0.022	0.021	**0.027**	0.024
	(0.18)	(0.18)	(0.19)	(0.19)	**(0.10)**	(0.13)
INF_t	**-0.216**	**-0.213**	**-0.236**	**-0.229**	**-0.264**	**-0.260**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
$ILLIQ_t$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.82)	(0.80)	(0.82)	(0.80)	(0.63)	(0.75)
$\ln ASV_t$	**-0.458**		**-0.577**		**-0.268**	
	(0.00)		**(0.00)**		**(0.04)**	
$\ln APV_t$					**-0.434**	
					(0.06)	
$\Delta \ln Y_t$	**-0.233**	**-0.233**	**-0.236**	**-0.236**	**-0.238**	**-0.241**
	(0.02)	**(0.03)**	**(0.02)**	**(0.02)**	**(0.01)**	**(0.02)**
Adj. R^2	0.159	0.162	0.166	0.169	0.171	0.181

Panel C. Predicting Growth in Private Investment

$\Delta \ln Y_{t+1}$ =	$\Delta \ln I_{t+1}$					
Decomposition	*Baseline definition*		*Carhart (1997) 4-factor*		*Campbell et al (2001)*	
Regression	7C.1	7C.2	7C.3	7C.4	7C.5	7C.6
$\ln AIV_t$	0.485		0.567		0.288	
	(0.46)		(0.39)		(0.74)	
$\ln \psi_t$		**0.929**		**1.058**		**1.031**
		(0.01)		**(0.02)**		**(0.01)**
ΔS_t	**-0.043**	**-0.045**	**-0.042**	**-0.045**	**-0.042**	**-0.044**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
$TERM_t$	**0.005**	**0.004**	**0.004**	**0.004**	**0.005**	**0.004**
	(0.01)	**(0.00)**	**(0.01)**	**(0.00)**	**(0.02)**	**(0.01)**
ΔTB_t	-0.001	-0.001	-0.000	-0.000	0.000	0.000
	(0.93)	(0.94)	(0.96)	(0.97)	(0.99)	(0.95)
DIV_t	-0.526	-0.225	-0.682	-0.407	-0.443	-0.374
	(0.42)	(0.68)	(0.29)	(0.46)	(0.59)	(0.49)
RET_t	0.067	0.073	0.067	0.074	0.067	0.079
	(0.18)	(0.11)	(0.18)	(0.11)	(0.17)	(0.09)
INF_t	0.295	0.247	0.277	0.218	0.278	0.172
	(0.50)	(0.57)	(0.53)	(0.61)	(0.57)	(0.70)
$ILLIQ_t$	**-0.020**	**-0.019**	**-0.020**	**-0.020**	**-0.020**	**-0.020**
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.00)**	**(0.01)**
$\ln ASV_t$	**-0.933**		**-1.068**		-0.883	
	(0.01)		**(0.01)**		(0.12)	
$\ln APV_t$					0.124	
					(0.92)	
$\Delta \ln Y_t$	0.057	0.061	0.058	0.062	0.058	0.062
	(0.43)	(0.41)	(0.43)	(0.41)	(0.43)	(0.41)
Adj. R^2	0.187	0.188	0.187	0.188	0.185	0.187

Table VIII. Stock returns idiosyncrasy Predicting Innovation and Productivity Growth

This table reports the regression results using stock returns idiosyncrasy to predict next quarter innovation intensity (Panel A), either growth in aggregate patent counts (Δln PAT_t) or in citation-weighted patent counts (Δln CIT_t) of all U.S. public companies, as well as next quarter productivity growth (Panel B), in either total factor productivity (ΔTFP_t) or labor productivity (ΔLP_t). Stock returns idiosyncrasy is defined with the baseline decomposition (equations [1]-[3]), Carhart's (1997) 4-factor model (equation [6]), or Campbell et al. (2001) decomposition (equation [7]). Controls include: change in credit spread (ΔS), term spread (*TERM*), change in the ten-year Treasury bond yields (ΔTB), Dividend yield (*DIV*), inflation (*INF*), excess market return (*RET*), stock market liquidity (*ILLIQ*), and, in regressions involving ln *AIV*, systematic return variation (ln *ASV*). Newey-West adjusted p-values are in parentheses. Boldface denotes a significance level of 10% or better. Variable definitions are in Appendix A.

Panel A. Predicting Innovation Growth with Idiosyncratic Variation

ΔY_{t+1} =	Δln PAT_{t+1}		Δln CIT_{t+1}		Δln PAT_{t+1}		Δln CIT_{t+1}		Δln PAT_{t+1}		Δln CIT_{t+1}	
Decomposition	*Baseline definition*				*Carhart (1997) 4-factor*				*Campbell et al (2001)*			
Regression	8A.1	8A.2	8A.3	8A.4	8A.5	8A.6	8A.7	8A.8	8A.9	8A.10	8A.11	8A.12
ln AIV_t	0.192		**10.325**		1.027		**13.509**		0.494		**13.043**	
	(0.91)		**(0.01)**		(0.59)		**(0.01)**		(0.80)		**(0.01)**	
ln ψ_t		**2.046**		**8.883**		**2.693**		**11.350**		**2.472**		**10.830**
		(0.01)		**(0.00)**		**(0.01)**		**(0.00)**		**(0.01)**		**(0.00)**
ΔS_t	**-0.038**	**-0.046**	**-0.061**	-0.055	**-0.037**	**-0.045**	**-0.060**	-0.050	**-0.036**	**-0.045**	-0.050	-0.046
	(0.04)	**(0.01)**	**(0.08)**	(0.11)	**(0.05)**	**(0.01)**	**(0.09)**	(0.16)	**(0.05)**	**(0.01)**	(0.14)	(0.17)
$TERM_t$	0.004	0.002	0.000	0.001	0.004	0.002	-0.001	0.001	0.003	0.002	-0.004	-0.003
	(0.35)	(0.50)	(0.99)	(0.84)	(0.36)	(0.50)	(0.89)	(0.88)	(0.32)	(0.66)	(0.43)	(0.67)
ΔTB_t	0.006	0.006	0.000	-0.000	0.006	0.007	0.004	0.003	0.008	0.008	0.013	0.010
	(0.68)	(0.65)	(0.99)	(0.99)	(0.65)	(0.61)	(0.82)	(0.87)	(0.58)	(0.53)	(0.50)	(0.61)
DIV_t	**-2.605**	-1.322	**9.581**	**8.570**	**-2.619**	-1.639	**8.568**	**7.280**	**-2.509**	-1.596	**7.528**	**7.437**
	(0.07)	(0.34)	**(0.01)**	**(0.00)**	**(0.07)**	(0.26)	**(0.01)**	**(0.00)**	**(0.10)**	(0.27)	**(0.03)**	**(0.00)**
RET_t	-0.080	-0.052	-0.273	-0.294	-0.080	-0.056	**-0.281**	**-0.311**	-0.072	-0.040	**-0.192**	**-0.243**
	(0.23)	(0.43)	(0.03)	(0.03)	(0.23)	(0.41)	**(0.03)**	**(0.03)**	(0.27)	(0.55)	**(0.10)**	**(0.08)**
INF_t	**0.937**	0.727	**1.344**	**1.501**	**0.875**	0.669	1.009	**1.264**	**0.831**	0.557	0.610	0.759
	(0.04)	(0.11)	**(0.05)**	**(0.05)**	**(0.05)**	(0.13)	(0.14)	**(0.09)**	**(0.07)**	(0.22)	(0.33)	(0.29)
$ILLIQ_t$	**0.066**	**0.070**	**0.087**	**0.084**	**0.067**	**0.069**	**0.083**	**0.080**	**0.065**	**0.067**	**0.067**	**0.070**
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**	**(0.00)**	**(0.01)**	**(0.02)**	**(0.02)**
ln ASV_t	**-2.075**		**-8.876**		**-2.727**		**-11.347**		**-1.782**		**-5.251**	
	(0.01)		**(0.00)**		**(0.01)**		**(0.00)**		**(0.03)**		**(0.00)**	
ln APV_t									-0.549		**-6.765**	
									(0.77)		**(0.00)**	
ΔlnY_t	**-0.765**	**-0.770**	**-0.637**	**-0.633**	**-0.766**	**-0.771**	**-0.654**	**-0.646**	**-0.765**	**-0.771**	**-0.650**	**-0.642**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
Adj. R^2	0.630	0.627	0.444	0.444	0.630	0.628	0.458	0.456	0.629	0.627	0.450	0.450

Panel B. Predicting Productivity Growth with Idiosyncratic Variation

ΔY_{t+1} =	ΔTFP_{t+1}		ΔLP_{t+1}		ΔTFP_{t+1}		ΔLP_{t+1}		ΔTFP_{t+1}		ΔLP_{t+1}	
Decomposition	*Baseline definition*				*Carhart (1997) 4-factor*				*Campbell et al (2001)*			
Regression	8A.1	8A.2	8A.3	8A.4	8A.5	8A.6	8A.7	8A.8	8A.9	8A.10	8A.11	8A.12
ln AIV_t	**0.859**		**1.148**		**0.962**		**1.245**		0.167		0.134	
	(0.10)		**(0.02)**		**(0.10)**		**(0.02)**		(0.76)		(0.79)	
ln ψ_t		0.502		0.212		0.572		0.241		0.468		-0.014
		(0.16)		(0.55)		(0.19)		(0.57)		(0.28)		(0.97)
ΔS_t	**-0.022**	**-0.021**	-0.012	-0.007	**-0.023**	**-0.021**	-0.012	-0.007	**-0.022**	**-0.021**	**-0.012**	-0.007
	(0.00)	**(0.00)**	(0.15)	(0.39)	**(0.00)**	**(0.00)**	(0.13)	(0.39)	**(0.00)**	**(0.00)**	**(0.10)**	(0.34)
$TERM_t$	0.003	0.003	0.000	0.001	0.003	0.003	-0.000	0.001	0.003	0.003	0.001	0.001
	(0.18)	(0.15)	(0.97)	(0.69)	(0.20)	(0.15)	(0.95)	(0.70)	(0.14)	(0.16)	(0.71)	(0.72)
ΔTB_t	-0.000	-0.000	-0.001	-0.001	-0.000	-0.000	-0.000	-0.001	-0.000	0.000	-0.001	-0.001
	(0.96)	(0.94)	(0.92)	(0.87)	(0.99)	(0.97)	(0.94)	(0.88)	(0.96)	(0.98)	(0.86)	(0.91)
DIV_t	**1.203**	**0.964**	**1.684**	1.051	**1.080**	0.865	**1.569**	1.009	**1.504**	0.888	**2.070**	1.031
	(0.02)	**(0.08)**	**(0.01)**	(0.12)	**(0.03)**	(0.11)	**(0.01)**	(0.13)	**(0.01)**	(0.10)	**(0.00)**	(0.13)
RET_t	**0.088**	**0.083**	0.040	0.027	**0.089**	**0.084**	0.042	0.027	**0.080**	**0.087**	0.028	0.028
	(0.02)	**(0.02)**	(0.17)	(0.37)	**(0.02)**	**(0.02)**	(0.13)	(0.36)	**(0.03)**	**(0.02)**	(0.33)	(0.35)
INF_t	**-0.585**	**-0.547**	**-0.719**	**-0.607**	**-0.609**	**-0.563**	**-0.747**	**-0.614**	**-0.535**	**-0.580**	**-0.630**	**-0.607**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
$ILLIQ_t$	-0.009	-0.010	-0.005	-0.007	-0.010	-0.010	-0.006	-0.007	-0.009	**-0.011**	-0.005	-0.008
	(0.20)	(0.18)	(0.37)	(0.30)	(0.17)	(0.15)	(0.33)	(0.28)	(0.27)	**(0.10)**	(0.44)	(0.15)
ln ASV_t	-0.501		-0.208		-0.567		-0.229		**-0.752**		-0.596	
	(0.18)		(0.56)		(0.21)		(0.60)		**(0.09)**		(0.20)	
ln APV_t									0.981		**1.445**	
									(0.13)		**(0.03)**	
$\Delta \ln Y_t$	-0.010	-0.012	0.001	0.015	-0.011	-0.012	-0.002	0.014	-0.008	-0.011	0.001	0.014
	(0.85)	(0.83)	(0.98)	(0.77)	(0.83)	(0.82)	(0.96)	(0.78)	(0.89)	(0.84)	(0.99)	(0.78)
Adj. R^2	0.149	0.150	0.064	0.049	0.149	0.150	0.066	0.049	0.149	0.148	0.071	0.048

Figure 1. Idiosyncratic and Systematic Variation over Business Cycles

Aggregate idiosyncratic variation, AIV_t, and aggregate systematic variation, ASV_t, are plotted against U.S. business cycles from 1926Q1 to 2020Q4. Detailed variable definitions are in Equations [1] to [3] and in Appendix A. Shaded areas denote NBER recessions.

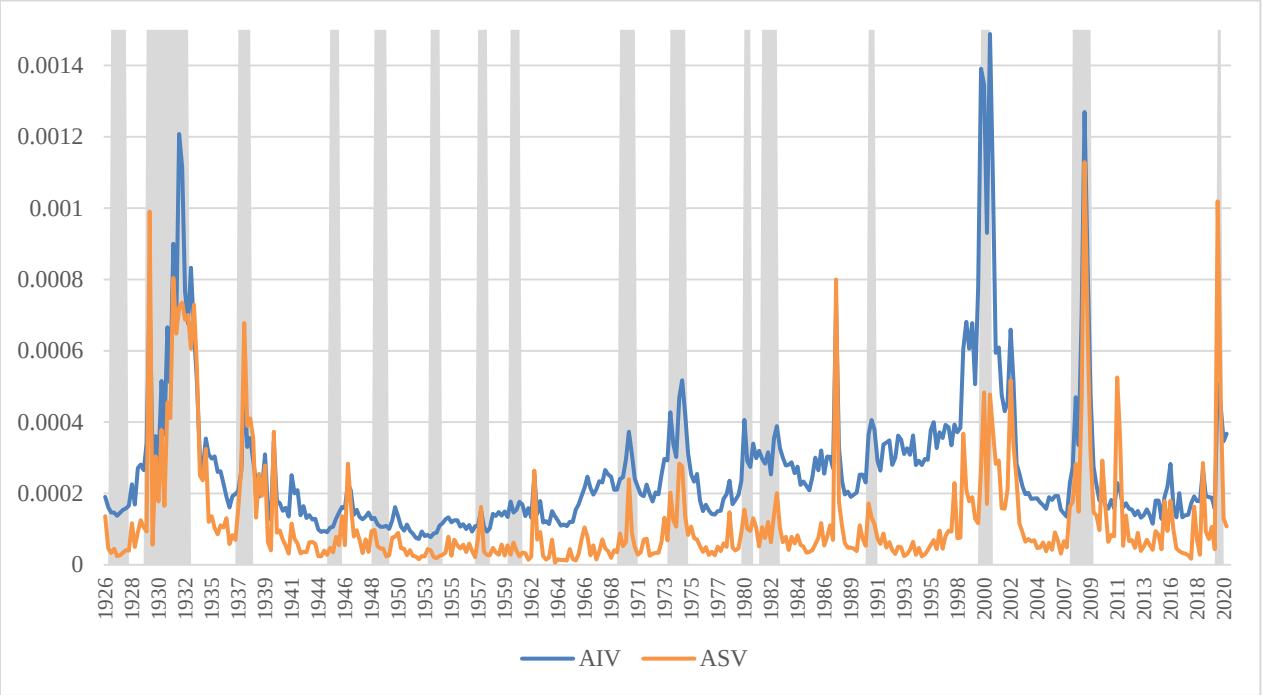
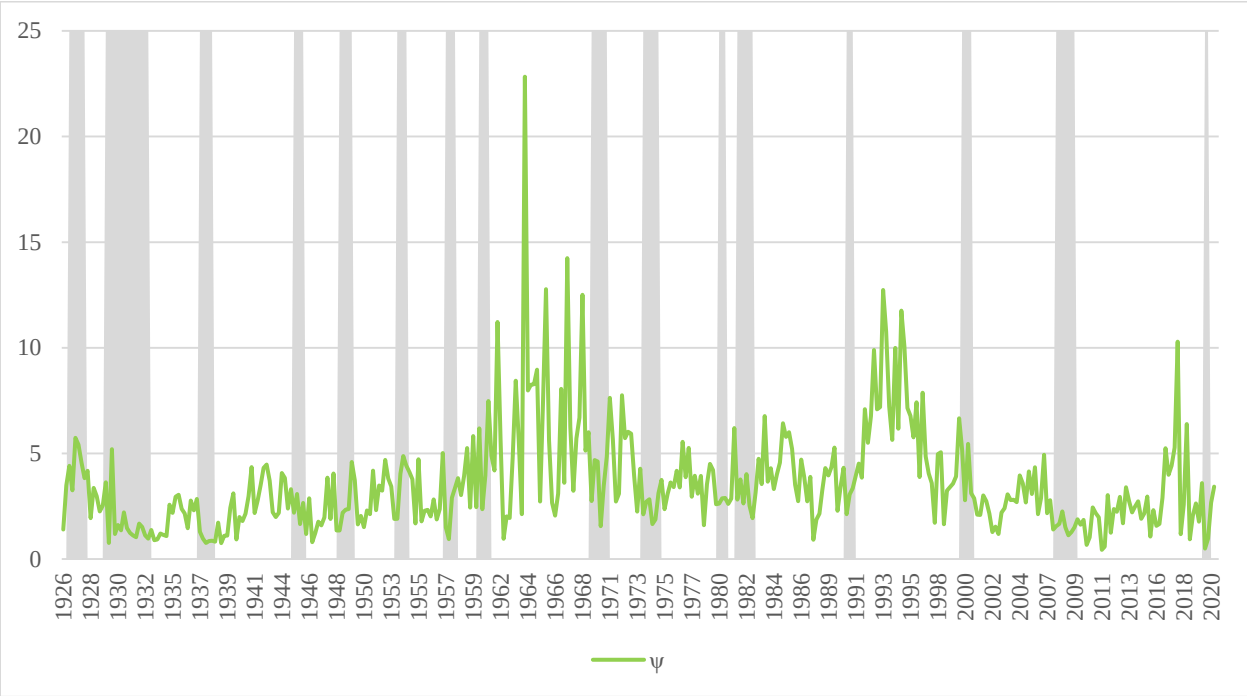


Figure 2. Relative Idiosyncratic Variation over Business Cycles

Relative idiosyncratic return variation, $\psi_t = AIV_t/ASV_t$, is plotted from 1926Q1 to 2020Q4. Detailed variable definitions are in Appendix A. Shaded areas denote NBER recessions.