JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 58, No. 8, Dec. 2023, pp. 3547–3576

doi:10.1017/S0022109022001417

Idiosyncrasy as a Leading Indicator

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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.

I. 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), and Vivarelli (2014)). Recent work adds institutional reforms (La Porta, Lopez-de-Silanes, and Shleifer (2008)), financial liberalizations (Henry (2007)), and market expansions (Aw, Roberts, and Xu (2011)) to the roster of productivity-enhancing shocks. Work in growth theory (Aghion and Howitt (1992)) and finance (Fogel, Morck, and Yeung (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

We thank Jennifer Conrad (the editor), Gill Segal (the referee), and David Vines for their helpful comments and suggestions.

idiosyncratic stock return 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. Bekaert 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 1947:Q1 to 2020:Q4.

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, Stein, and Zakrajšek (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, Lettau, Malkiel, and Xu (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 (see, e.g., Hamilton and Lin (1996), Choudhry, Papadimitriou, and Shabi (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 return 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 return variance does not forecast growth in government spending.

Another possibility is that disequilibration alters household-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 return 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 toward investment in innovation (Stein and Stone (2013)). We find that higher idiosyncratic stock return 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 return 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 return variation:

- 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.
- Forecasting higher next-quarter growth in aggregate output and investment in innovation because disequilibrating shocks most often reflect technological progress and creative destruction.
- 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.

II. Variables Definition and Data Summary

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

A. Measures of Stock Returns Idiosyncrasy and Macroeconomic Growth

Stock return variation is decomposed into a systematic and a firm-specific component using the following regression (Roll (1988), Morck, Yeung, and Yu (2000)):

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

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 $\text{SSE}_{j,t} \equiv \frac{1}{N_{j,t}-1} \sum_{s \epsilon t} \varepsilon_{j,s}^2$ 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 $\text{SSE}_{j,t}$ each quarter,

$$\text{AIV}_t \equiv \sum_j w_{j,t} \text{SSE}_{j,t}, \tag{2}$$

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 $\text{SSM}_{j,t}$ 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 $\text{SSM}_{j,t}$ each quarter

$$\text{ASV}_t \equiv \sum_{\mathrm{j}} w_{j,t} \text{SSM}_{j,t}. \tag{3}$$

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 $\psi_t \equiv \text{AIV}_t / \text{ASV}_t$.

The tests below forecast next-quarter macroeconomic growth rates, defined as log differences in real GDP, $\Delta\ln(\text{GDP}_{t+1})$, or real industrial production, $\Delta\ln(\text{IP}_{t+1})$. The forecasting variables of primary interest in these tests are natural logarithms of aggregate idiosyncratic variation, $\ln(\text{AIV}_t)$, or relative idiosyncratic variation, $\ln(\psi_t) \equiv \ln(\text{AIV}_t) - \ln(\text{ASV}_t)$.

B. Controlling for Other Leading Indicators

Variables found elsewhere to predict economic conditions, measured quarterly, are: i) change in credit spread, ΔS, the change in the premium of Baa industrial bond yield over 10-year T-bond yield (López-Salido et al. (2017), Bordalo, Gennaioli, and Shleifer (2018), Chang et al. (2021)); ii) term spread, TERM, the 10-year T-bond yield minus the 3-month T-bill rate (Harvey (1988), Estrella and Hardouvelis (1991)); iii) ΔTB, the change in 10-year T-bond yield (Stock and Watson (1989), Estrella and Mishkin (1998), and Diebold, Rudebusch, and Aruoba (2006)); iv) dividend yield, DIV, the quarterly cumulative dividend yield of the value-weighted CRSP stock portfolio (Fama and French (1989), Chen (1991)); v) the excess market return, RET, the value-weighted CRSP market index return minus the 3-month T-bill yield (Fama (1981), Barro (1990)); vi) inflation, INF, the quarterly percentage change in the Consumer Price Index (CPI) (Fischer (1993), Barro (1995)); and vii) stock market illiquidity, ILLIQ, the equal-weighted mean Amihud (2002) illiquidity measure (absolute return divided by the dollar volume) across all common stocks (Næs et al. (2011), Switzer and Picard (2016)) and stock market volatility (Schwerz (1989), Bloom (2009)), $\ln(\text{ASV}_t)$, defined as in (2).[1]

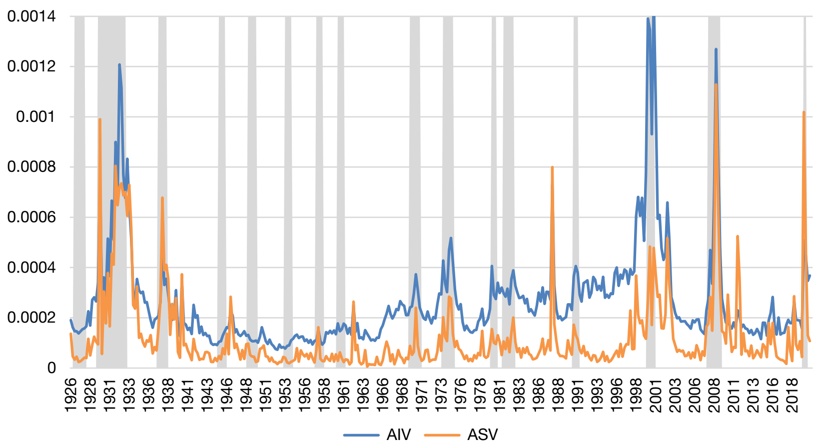
C. Data Summary

Figure 1 graphs quarterly aggregate idiosyncratic, AIV_t and systematic, ASV_t, variation from 1926:Q1 to 2020:Q4, the shaded areas indicating NBER recessions. Both measures move counter-cyclically. Two patterns deserve notice. First, the

FIGURE 1

Idiosyncratic and Systematic Variation over Business Cycles

Figure 1 plots aggregate idiosyncratic variation (AIV_t) and aggregate systematic variation (ASV_t) against U.S. business cycles from 1926:Q1 to 2020:Q4. Detailed variable definitions are in equations (1)–(3) and in the Appendix. Shaded areas denote NBER recessions.

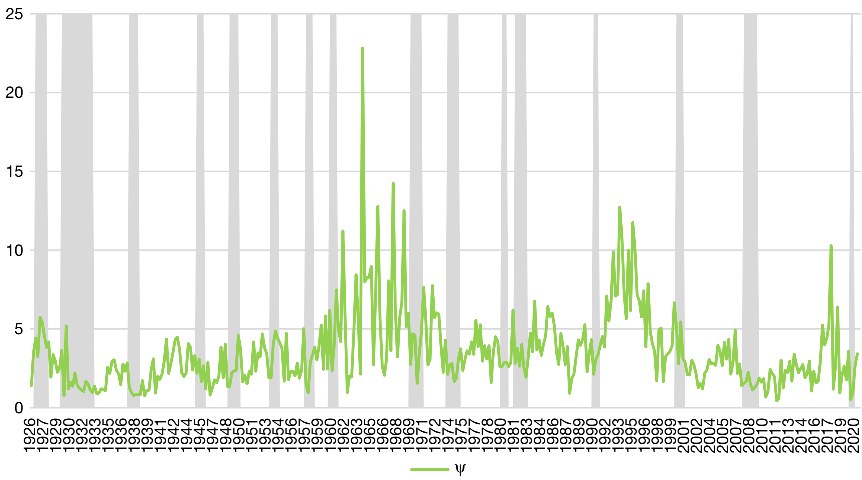


[1]All variables pass the Dickey–Fuller Generalized Least Squares (DF-GLS) unit root test, except for stock market illiquidity. The first-order differenced illiquidity series is used in subsequent tests.

FIGURE 2

Relative Idiosyncratic Variation over Business Cycles

Figure 2 plots relative idiosyncratic return variation (ψ_t = AIV$_t$/ASV$_t$) from 1926:Q1 to 2020:Q4. Detailed variable definitions are in the Appendix. Shaded areas denote NBER recessions.



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, ψ_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 1935 and 1937 to 1939) 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.

Table 1 reports summary statistics for the stock return variation measures, macroeconomic growth rates, and control variables over the sample period of 1947: Q1 to 2020:Q4. Table 2 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

TABLE 1

Summary Statistics

Table 1 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 1947:Q1 to 2020:Q4. Both AIV_t and ASV_t are multiplied by 1,000. See the Appendix 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
$\Delta\ln(GDP_{t+1})$	295	0.008	0.012	−0.009	0.008	0.023
$\Delta\ln(IP_{t+1})$	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 2

Correlation Matrix

Table 2 reports the Pearson correlation coefficients between the variables used in the analysis over 295 quarters from 1947:Q1 to 2020:Q4. p-values are reported in parentheses. Boldface denotes significance at the 10% level or better. See the Appendix 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)

(Stock and Watson (1989), Schwerz (1989), Næs et al. (2011), and López-Salido et al. (2017)).

III. 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 alternative 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.

A. Baseline Next Quarter Predictive Regressions

Table 3 summarizes results from our baseline regression (4) for testing how well stock return idiosyncrasy in quarter t predicts macroeconomic growth in quarter $t+1$,

TABLE 3

Predicting Economic Growth with Stock Returns Idiosyncrasy

Table 3 predicts next quarter economic growth with current quarter stock returns idiosyncrasy over 294 quarters from 1947:Q1 to 2020:Q4. Panel A reports regressions using quarter t aggregate idiosyncratic stock return variation, ln(AIV$_t$), to predict quarter $t+1$ GDP growth, $\Delta\ln(\text{GDP}_{t+1})$, or industrial production growth, $\Delta\ln(\text{IP}_{t+1})$. 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 the Appendix, are: change in credit spread (ΔS), term spread (TERM), change in the 10-year T-bond yields(ΔTB), 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(AIV$_t$) and ln(ASV$_t$) in each Panel A specification with their ratio $\ln(\psi_t) = \ln(\text{AIV}_t) - \ln(\text{ASV}_t)$. 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% or better.

Panel A. Idiosyncratic Return Variation Predicting Next Quarter Economic Growth

Decomposition	Baseline Definition		Carhart 4-Factor		Campbell et al.	
$\Delta\ln(Y_{t+1})$ =	$\Delta\ln(\text{GDP}_{t+1})$	$\Delta\ln(\text{IP}_{t+1})$	$\Delta\ln(\text{GDP}_{t+1})$	$\Delta\ln(\text{IP}_{t+1})$	$\Delta\ln(\text{GDP}_{t+1})$	$\Delta\ln(\text{IP}_{t+1})$
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)
Δln(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

(continued on next page)

TABLE 3 (continued)

Predicting Economic Growth with Stock Returns Idiosyncrasy

Panel B. Relative Idiosyncratic Variation Predicting Next Quarter Growth

Decomposition	Baseline Definition		Carhart 4-Factor		Campbell et al.	
$\Delta\ln(Y_{t+1})$ =	$\Delta\ln(GDP_{t+1})$	$\Delta\ln(IP_{t+1})$	$\Delta\ln(GDP_{t+1})$	$\Delta\ln(IP_{t+1})$	$\Delta\ln(GDP_{t+1})$	$\Delta\ln(IP_{t+1})$
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

$$(4)\quad \Delta\ln(Y_{t+1}) = a + b\ln(\text{AIV}_t) + b_1\Delta S_t + b_2\text{TERM}_t + b_3\Delta\text{TB}_t + b_4\text{DIV}_t + b_5\text{RET}_t + b_6\text{INF}_t + b_7\text{ILLIQ}_t + b_8\ln(\text{ASV}_t) + b_9\Delta\ln(Y_t) + e_t,$$

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 Section II.B.

Panel A of Table 3 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 $\ln(\text{AIV}_t)$ predicting statistically and economically significantly faster next-quarter growth in real GDP and real industrial production using data the whole same period of 1947:Q1 to 2020:Q4. Specifically, a 1-standard-deviation increase in current-quarter $\ln(\text{AIV}_t)$ 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.

B. Rejecting Econometric Artifacts

Before proceeding further, we confirm that econometric artifacts do not explain Table 3. To save space, some tests in this section are tabulated in the Supplementary Material.

[2]The coefficients of ln(AIV) and $\ln(\psi_t)$ 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 3, $\ln(\text{AIV}_t)$ and $\ln(\text{ASV}_t)$ are jointly significant.

First, the Table 3 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 production growth.[3] $\ln(\text{AIV}_t)$ 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, $\ln(\text{ASV}_t)$, 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), and Alessandri and Mumtaz (2019)). However, the high correlation of $\ln(\text{AIV}_t)$ with $\ln(\text{ASV}_t)$ ($\rho = 0.706, p < 0.01$) in Table 2 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 $\ln(\text{AIV}_t)$ from the regressions in Table 3 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 3 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 1 quarter later, idiosyncratic variation would spuriously appear to predict higher next quarter growth in Table 3. Panel A of Table A1 in the Supplementary Material 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. Panel B of Table A1 in the Supplementary Material summarizes regressions analogous to (4), but explaining contemporaneous $\Delta \ln(Y_t)$, rather than forecasting next-quarter $\Delta \ln(Y_{t+1})$. In these, $\ln(\text{ASV}_t)$ attracts a significant negative coefficient, consistent with high systematic volatility in downturns; however, $\ln(\text{AIV}_t)$ attracts a positive insignificant coefficient. This is inconsistent with mean reversion driving the results in Table 3. Finally, if high $\ln(\text{AIV}_t)$ 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 3 but forecasting current-plus-next-quarter output growth, $\Delta \ln(Y_{t+1}) + \Delta \ln(Y_t)$. Inconsistent with mean reversion driving our findings, Panel C of Table A1 in the Supplementary Material shows $\ln(\text{AIV}_t)$ attracting a significant positive coefficient in these tests.

C. Robustness to Alternative Stock Return Variance Decomposition

The decomposition of stock return variation is described in Section II.A is simple and follows Morck et al. (2000) and numerous other papers that use their

[3]Dropping some of the control variables weakens the statistical significance, but the coefficient of $\ln(\text{AIV}_t)$ remains significant in the regressions predicting GDP growth.

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 4-factor model:

$$R_{j,s} - R_{f,s} = \alpha_{j,t} + \beta_{j,t}\left(R_{M,s} - R_{f,s}\right) + s_{j,t}\mathrm{SMB}_s + h_{j,t}\mathrm{HML}_s + m_{j,t}\mathrm{UMD}_s + \epsilon_{j,s}, \tag{5}$$

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:

$$\begin{aligned} \mathrm{ASV}_t &= \sum_{s\in t}\left(R_{m,s} - \overline{R}_{m,t}\right)^2, \\ \mathrm{APV}_t &= \sum_i w_{i,t}\sum_{s\in t}\left(R_{i,s} - R_{m,s}\right)^2, \\ \mathrm{AIV}_t &= \sum_j w_{j,t}\sum_{s\in t}\left(R_{j,s} - R_{i,s}\right)^2, \end{aligned} \tag{6}$$

where $R_{m,s}$ is the value-weighted market index return on day s, $\overline{R}_{m,t}$ is the average daily market index return in quarter t, $R_{i,s}$ is the return of 2-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 III.A and following Morck et al. (2000), uses the natural logarithms of relative idiosyncratic variation, $\ln(\psi_t)$. Panel B of Table 3 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 $t+1$,

$$\begin{aligned} \Delta\ln(Y_{t+1}) = a + b\ln(\psi_t) + b_1\Delta S_t + b_2\mathrm{TERM}_t + b_3\Delta\mathrm{TB}_t + b_4\mathrm{DIV}_t \\ + b_5\mathrm{RET}_t + b_6\mathrm{INF}_t + b_7\mathrm{ILLIQ}_t + b_9\Delta\ln(Y_t) + e_t, \end{aligned} \tag{7}$$

where all variables are as in (4). This constrains the coefficient of $\ln(\mathrm{AIV}_t)$ to be minus 1 times that of $\ln(\mathrm{ASV}_t)$, 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.

D. Robustness to Alternative Measure of Economic Activity

The tests in Sections III.A, B, and C 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.

TABLE 4

Stock Returns Idiosyncrasy Predicting Alternative Economic Growth Measures

Table 4 reports regressions using stock returns idiosyncrasy to predict alternative measures of improving economic conditions. Stock returns idiosyncrasy is either ln(AIV$_t$) or ln(ψ_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, APV$_t$. Control variables are: change in credit spread (ΔS), term spread (TERM), change in 10-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 the Appendix.

$\Delta\ln(Y_{t+1})$ =	CFNAI$_{t+1}$					
Decomposition	Baseline Definition		Carhart 4-Factor		Campbell et al.	
Regression	4.1	4.2	4.3	4.4	4.5	4.6
ln(AIV$_t$)	**0.084**		**0.125**		0.143	
	(0.05)		**(0.01)**		(0.12)	
ln(ψ_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

The Chicago Fed's National Activity Index (CFNAI) is a monthly comprehensive economic activity index based on 85 economic activity series. A 3-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 4 summarizes 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) 4-factor model, or the Campbell et al. (2001) model predicts higher national economic activity. The even-numbered regressions repeat this exercise measuring

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

https://doi.org/10.1017/S0022109022001417 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109022001417 Published online by Cambridge University Press

idiosyncratic variation by the ratio of idiosyncratic to systematic return variation, $\ln(\psi_t)$. This ratio significantly predicts CFNAI across all three specifications.

E. 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:

$$\text{(8)} \quad \Delta \ln(Y_t) = \alpha + \sum_{i=1}^{k} \delta_{t-i} \Delta \ln(Y_{t-i}) + \sum_{i=1}^{k} \beta_{t-i} \ln(\mathrm{AIV}_{t-i}) + \sum_{i=1}^{k} \gamma_{t-i} X_{t-i} + \epsilon_t,$$

$$\text{(9)} \quad \ln(\mathrm{AIV}_t) = a + \sum_{i=1}^{k} d_{t-i} \Delta \ln(Y_{t-i}) + \sum_{i=1}^{k} b_{t-i} \ln(\mathrm{AIV}_{t-i}) + \sum_{i=1}^{k} c_{t-i} X_{t-i} + \epsilon_t,$$

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 10-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, $\ln(\mathrm{ASV})$. 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 5 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.

F. Forecasting Economic Growth Out-of-Sample

The tests throughout Section III show 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 growth up to 4 quarters following the in-sample estimation window. Stock returns idiosyncrasy is shown to have significant out-of-sample forecasting power.

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

TABLE 5

Economic Growth and Stock Returns Idiosyncrasy: Granger Causality Tests

Table 5 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^2statistics 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^2statistics and p-values for each variable's set of lags. Control variables are as in Table 3: change in credit spread (ΔS), term spread (TERM), change in the 10-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 the Appendix.

	Granger Causing Economic Growth				Granger Causing Stock Returns Idiosyncrasy			
	$\Delta\ln(\text{GDP}_t)$		$\Delta\ln(\text{IP}_t)$		$\ln(\text{AIV}_t)$		$\ln(\psi_t)$	
Predictor	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8
$\Delta\ln(\text{GDP}_{t-k \text{ to } t-1})$	7.83 (0.16)	7.28 (0.20)			5.30 (0.38)		3.61 (0.61)	
$\Delta\ln(\text{IP}_{t-k \text{ to } t-1})$			**22.00** **(0.00)**	**18.37** **(0.00)**		6.16 (0.29)		4.99 (0.42)
$\ln(\text{AIV}_{t-k \text{ to } t-1})$	**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)
$\text{TERM}_{t-k \text{ to } t-1}$	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)
$\Delta\text{TB}_{t-k \text{ to } t-1}$	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)
$\text{DIV}_{t-k \text{ to } t-1}$	**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)
$\text{RET}_{t-k \text{ to } t-1}$	**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)
$\text{INF}_{t-k \text{ to } t-1}$	**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)
$\text{ILLIQ}_{t-k \text{ to } t-1}$	**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)
$\ln(\text{ASV}_{t-k \text{ to } t-1})$	**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

The unrestricted in-sample regression is:

$$\Delta\ln(Y_{t+h}) = \alpha + \sum_{k=0}^{n}\beta_{t-k}\ln(\text{AIV}_{t-k}) + \sum_{k=0}^{n}\gamma_{t-k}X_{t-k} + \sum_{k=0}^{n}\delta_{t-k}\Delta\ln(Y_{t-k}) + \sum_{k=0}^{n}\beta'_{t-k}\ln(\text{ASV}_{t-k}) + \varepsilon_{t+h}, \tag{10}$$

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 II.B, 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 $\sum_{k=0}^{n}\beta_{t-k}\ln(\text{AIV}_{t-k}) + \sum_{k=0}^{n}\beta'_{t-k}\ln(\text{ASV}_{t-k})$.

Regression (10) is estimated recursively, starting with a 100-quarter window from 1947:Q1 through 1971:Q4. The estimation window then expands 1 quarter as the forecasting point moves 1 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)).

$$\text{MSE} - \text{F} \equiv (p-h+1)\frac{\text{MSE}_r - \text{MSE}_u}{\text{MSE}_u}, \tag{11}$$

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 1-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

$$\text{ENC} - \text{NEW} = (p-h+1)\frac{\sum_{t+h}\left(\epsilon^2_{r,t+h} - \epsilon_{r,t+h}\epsilon_{u,t+h}\right)}{\sum_{t+h}\epsilon^2_{u,t+h}}, \tag{12}$$

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 6 reports the MSE-F and ENC-NEW test statistics, with forecast horizons from 1 to 4 quarters out. In the 1-quarter-ahead forecasts ($h = 1$), both ln(AIV) and $\ln(\psi)$ significantly improve the accuracy in forecasting the growth rates of real GDP and of industrial production. All MSE-F test statistics, except for predicting industrial production growth with the baseline ln(AIV), are significant at the 10% level or better. ENC-NEW statistics are significant for all specifications using $\ln(\psi)$ and also significant for ln(AIV) defined using the 4-factor model.

The forecasting performance of idiosyncrasy remains strong when the forecast horizon is extended to 2 to 4 quarters (h = 2 or 3). Both MSE-F and ENC-NEW statistics are significant at 10% or better for models predicting $\Delta\ln(\text{IP}_{t+2})$. Both test statistics are also significant in all but one the models predicting $\Delta\ln(\text{GDP}_{t+3})$ or $\Delta\ln(\text{IP}_{t+3})$. As the forecast horizon increases to 4 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 3 quarters ahead.

IV. 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

TABLE 6

Forecasting Future Economic Growth with Idiosyncrasy Out-of-Sample

Table 6 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 1947:Q1 to 1971:Q4. The window expands 1 quarter at a time as the forecasting point moves 1 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 10-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 1 to 4 quarters. Critical test values are from Clark and McCracken (2001). Boldface denotes a significance level of 10% or better. Variable definitions are in the Appendix.

	Baseline Definition				Carhart 4-Factor				Campbell et al.			
$\Delta\ln(Y_{t+h})$ =	$\Delta\ln(GDP_{t+h})$		$\Delta\ln(IP_{t+h})$		$\Delta\ln(GDP_{t+h})$		$\Delta\ln(IP_{t+h})$		$\Delta\ln(GDP_{t+h})$		$\Delta\ln(IP_{t+h})$	
	$\ln(AIV_{t-k\text{ to }t-1})$	$\ln(\psi_{t-k\text{ to }t-1})$	$\ln(AIV_{t-k\text{ to }t-1})$	$\ln(\psi_{t-k\text{ to }t-1})$	$\ln(AIV_{t-k\text{ to }t-1})$	$\ln(\psi_{t-k\text{ to }t-1})$	$\ln(AIV_{t-k\text{ to }t-1})$	$\ln(\psi_{t-k\text{ to }t-1})$	$\ln(AIV_{t-k\text{ to }t-1})$	$\ln(\psi_{t-k\text{ to }t-1})$	$\ln(AIV_{t-k\text{ to }t-1})$	$\ln(\psi_{t-k\text{ to }t-1})$
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**

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.

A. Forecasting Government Spending Growth

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

Panel A of Table 7 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 3. These tests, presented in Table A2 in the Supplementary Material, show that high stock returns idiosyncrasy helps forecast growth in private sector components of aggregate output.

B. 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 et al. (2016) associate increased idiosyncratic stock return risk with increased dispersion in household-level consumption growth.

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 B of Table 7 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.

Mean reversion – that is, higher idiosyncratic variation depressing current growth, which then rebounds generating spuriously higher next-quarter growth – is also rejected for consumption growth. Table A4 in the Supplementary Material summarizes mean reversion tests for consumption growth analogous to those for GDP growth in Table A1 in the Supplementary Material. Simple correlation in Panel A of Table A4 in the Supplementary Material shows that consumption growth ($\Delta\ln(C_t)$) is negatively correlated with contemporaneous idiosyncratic (ln(AIV)) and systematic return variations (ln(ASV)). The negative correlation with ln(ASV) is more than twice as large as the correlation with ln(AIV), resulting in a positive correlation between contemporaneous consumption growth and the ratio of idiosyncratic to systematic variation ($\ln(\psi)$). Panel B of Table A4 in the Supplementary Material shows that ln(AIV) attracts a positive and significant coefficient in regressions explaining contemporaneous consumption growth. Panel C of Table A4 in the

[6]We thank the referee for suggesting this exercise.

TABLE 7

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

Table 7 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 1947:Q1 to 2020:Q4. 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 10-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 ($\ln(\mathrm{ASV}_t)$). Variable definitions are in the Appendix. 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
$\ln(\mathrm{AIV}_t)$	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)
$\Delta\mathrm{TB}_t$	−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)
$\ln(\mathrm{ASV}_t)$	0.079		0.143		−0.150	
	(0.50)		(0.38)		(0.21)	
$\ln(\mathrm{APV}_t)$					**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
$\ln(\mathrm{AIV}_t)$	**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)
$\Delta\mathrm{TB}_t$	−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)
$\ln(\mathrm{ASV}_t)$	**−0.458**		**−0.577**		**−0.268**	
	(0.00)		**(0.00)**		**(0.04)**	
$\ln(\mathrm{APV}_t)$					**−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

(continued on next page)

https://doi.org/10.1017/S0022109022001417 Published online by Cambridge University Press

TABLE 7 (continued)

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

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 (0.46)		0.567 (0.39)		0.288 (0.74)	
$\ln(\psi_t)$		**0.929** **(0.01)**		**1.058** **(0.02)**		**1.031** **(0.01)**
ΔS_t	**−0.043** **(0.00)**	**−0.045** **(0.00)**	**−0.042** **(0.00)**	**−0.045** **(0.00)**	**−0.042** **(0.00)**	**−0.044** **(0.00)**
$TERM_t$	**0.005** **(0.01)**	**0.004** **(0.00)**	**0.004** **(0.01)**	**0.004** **(0.00)**	**0.005** **(0.02)**	**0.004** **(0.01)**
ΔTB_t	−0.001 (0.93)	−0.001 (0.94)	−0.000 (0.96)	−0.000 (0.97)	0.000 (0.99)	0.000 (0.95)
DIV_t	−0.526 (0.42)	−0.225 (0.68)	−0.682 (0.29)	−0.407 (0.46)	−0.443 (0.59)	−0.374 (0.49)
RET_t	0.067 (0.18)	0.073 (0.11)	0.067 (0.18)	0.074 (0.11)	0.067 (0.17)	0.079 (0.09)
INF_t	0.295 (0.50)	0.247 (0.57)	0.277 (0.53)	0.218 (0.61)	0.278 (0.57)	0.172 (0.70)
$ILLIQ_t$	**−0.020** **(0.01)**	**−0.019** **(0.01)**	**−0.020** **(0.01)**	**−0.020** **(0.01)**	**−0.020** **(0.00)**	**−0.020** **(0.01)**
$\ln(ASV_t)$	**−0.933** **(0.01)**		**−1.068** **(0.01)**		−0.883 (0.12)	
$\ln(APV_t)$					0.124 (0.92)	
$\Delta\ln(Y_t)$	0.057 (0.43)	0.061 (0.41)	0.058 (0.43)	0.062 (0.41)	0.058 (0.43)	0.062 (0.41)
Adj. R^2	0.187	0.188	0.187	0.188	0.185	0.187

Supplementary Material shows that idiosyncratic variation is also positively related to higher current-plus-next-quarter consumption growth, $\Delta\ln(C_{t+1})+\Delta\ln(C_t)$.

These findings accord 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]

C. Forecasting Investment Growth

We posit that disequilibration changes forward-looking equity prices idiosyncratically to reflect new information about firms' prospects. If firms with improved

[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. This juxtaposition suggests higher AIV might forecast decreased consumption growth in the more distant future. Higher AIV forecasts higher consumption growth up to 8 quarters ahead, but with attenuating significance and smaller coefficients. This might reflect attenuation bias or negatively shocked households beginning to cut back on their consumption. See Table A5 in the Supplementary Material.

prospects increased their investment and firms with diminished prospects delayed disinvesting, the next-quarter aggregate investment might rise. However, Panel C of Table 7 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 considerations govern the timing of investments. Growth option values rise with risk (Brennan and Schwarz (1985)), spurring aggregate investment. However, using more involved real options models, Bloom (2009) uses real options to explain increased micro-uncertainty predicting investment downturns. Moreover, 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).[8]

Another possibility is Chang et al.'s ((2021), fig. 6) finding associating higher idiosyncratic stock return variation, after adjustments for imputed option values of credit risk, with increased investment growth for more creditworthy firms, but reduced investment growth for higher credit-risk firms. Heterogeneity in credit risk (or other firm characteristics) across firms and time might thus aggregate to leave AIV insignificant in predicting aggregate investment.[9]

Yet another might be managers waiting for market signals before making major decisions, such as substantially boosting investment. In times of greater flux, evident as elevated firm-specific stock return variation, more managers might postpone decisions to await clearer market signal and to observe market reaction to other firms' decisions (see, e.g., Hawk, Pacheco-de-Almeida, and Yeung (2013), Décaire and Wittry (2022)).

More prosaic explanations also have empirical support. For example, managers more insulated from shareholder value maximization pressure delay downsizing to preserve private benefits from their corporate empires (Daley, Mehrotra, and Sivakumar (1997), Chen and Feldman (2018), and Myers and Lambrecht (2022)).

These explanations all posit a disequilibrating shock altering firms' subsequent investment heterogeneously, causing immediate idiosyncratic movements in forward-looking stock prices, but not necessarily boosting next-quarter aggregate investment.

Bachmann and Bayer (2014) report a strong pro-cyclicality in the cross-sectional dispersion of firm-level investment rates. We also find investment rate

[8]This suggests elevated idiosyncratic risk might forecast faster investment growth after a delay. Additional tests (see Table A6 in the Supplementary Material) fail to find this.

[9]Chang et al. ((2021), fig. 4) also report no clear pattern after increased idiosyncratic volatility unadjusted for imputed option value of credit risk. This suggests an investment channel operating through different firms differently. Further research into firm-level heterogeneity might reveal more insights.

dispersion positively correlated with stock return idiosyncratic variation ($\rho = 0.21$, p-value = 0.02).[10] 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 3 and Panel C of Table 7 using investment dispersion instead of AIV leave the former insignificant in predicting GDP growth and marginally significant in predicting industrial production growth. Moreover, 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)). Table A3 in the Supplementary Material summarizes these results.[11]

D. Forecasting Innovation and Productivity Growth

Another possibility is that Section IV.C considers the wrong sort of investment. 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 7.

Panel A of Table 8 indeed show higher stock returns idiosyncrasy predicting increased next-quarter innovation intensity, measured as quarterly growth (log differences) in simple, $\Delta\ln(\text{PAT}_t)$, or citation-weighted, $\Delta\ln(\text{CIT}_t)$, patent counts aggregated across U.S. listed firms from 1947:Q1 to 2016:Q4, as in Kogan, Papanikolaou, Seru, and Stoffman (2017).[12] Higher stock returns idiosyncrasy, measured as either aggregate, $\ln(\text{AIV}_t)$, 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 8 shows that elevated stock returns idiosyncrasy, ln(AIV), predicts next-quarter growth in business sector total factor productivity (ΔTFP) and labor productivity (ΔLP) over 1947:Q1 to 2020:Q4.[13] The idiosyncrasy ratio, however, fails to attain significance. Note that $\ln(\text{AIV}_t)$ predicts subsequent quarter productivity growth above and beyond predictability by leading indicators used in

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

[11] 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 3 regressions.

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

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

TABLE 8

Stock Returns Idiosyncrasy Predicting Innovation and Productivity Growth

Table 8 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 10-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 the Appendix.

Panel A. Predicting Innovation Growth with Idiosyncratic Variation

Decomposition	Baseline Definition				Carhart (1997) 4-Factor				Campbell et al. (2001)			
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$_{t+1}$)	
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)**	
Δln(Y$_t$)	**−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

(continued on next page)

https://doi.org/10.1017/S0022109022001417 Published online by Cambridge University Press

TABLE 8 (continued)

Stock Returns Idiosyncrasy Predicting Innovation and Productivity Growth

Panel B. Predicting Productivity Growth with Idiosyncratic Variation

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

prior studies. Higher dividend yield (DIV), higher market excess return (RET), and lower inflation (INF) also predict higher next-quarter productivity growth.

V. Conclusions

Our findings support adding stock return idiosyncrasy 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 1 to 3 quarters ahead.

Our results build upon important prior results in several ways. First, prior work shows firm-level heterogeneity in, for example, 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 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) finds a positive relation between return dispersion and future market volatility, suggesting return dispersion containing useful information about the future economic state. Garcia, Mantilla-Garcia, and Martellini (2014) correctly note that cross-section return 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, for example, Alfaro et al. (2018), we find increased systematic stock return variation to forecast reduced output growth and its subcomponents 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 return 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 approach instead explicitly follows 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. In contrast, 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)). Further empirical and theoretical work along these lines might be fruitful.[14]

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. Segal (2019) distinguish growth-promoting investment shocks from growth-inhibiting consumption shocks. Such dichotomies parallel 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)). That is, our findings are also consistent with most historical shocks redistributing firms' investment opportunities, evident in increased firm-specific stock return variation, to allow increased investment in innovation, which on net increases next-quarter consumption growth and GDP growth.

Appendix. Variable Definitions and Data Sources

AIV_t: Aggregate idiosyncratic variation 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 $\text{SSE}_{j,t}$, the sum of squared residual variation in the time-series regression $R_{j,s} = \alpha_{\varphi,\tau}\, \beta_{j,t}\, R_{m,s} + \varepsilon_{j,s}$, where $R_{j,s}$ and $R_{m,s}$ are total returns of stock j and the market, respectively, on day s in quarter t. Source: CRSP, University of Chicago.

[14]Elevated idiosyncratic stock return variation forecasting faster consumption and innovation growth may have implications for empirical and theoretical tensions regarding the pricing of idiosyncratic risk and market incompleteness (e.g., Ang et al. (2006), Di Tella and Hall (2022)).

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 $\mathrm{SSM}_{j,t}$, the sum of squared explained variation in stock-level time-series regressions used to obtain $\mathrm{SSE}_{j,t}$. Source: CRSP.

ψ_t: Relative idiosyncrasy in quarter t is AIV_t / ASV_t. Source: CRSP.

$\Delta\ln(\mathrm{GDP}_t)$: GDP growth is log difference in seasonally adjusted real GDP between quarter t and $t-1$. Source: Bureau of Economic Analysis (BEA).

$\Delta\ln(\mathrm{IP}_t)$: 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. Source: Federal Reserve Bank of St. Louis Economic Data (FRED).

$\Delta\ln(C_t)$: Consumption growth is the log difference in real personal consumption expenditures between quarter t and $t-1$. Source: BEA.

$\Delta\ln(G_t)$: Government spending growth is the log difference in real government spending between quarter t and $t-1$. Source: BEA.

$\Delta\ln(I_t)$: Investment growth is the log difference in private nonresidential fixed investment between quarter t and $t-1$. Source: BEA.

ΔS_t: Change in credit spread, Baa rated bond yields minus 10-year government bond yields, from quarter $t-1$ to t. Quarterly rates are average of respectively monthly rates within each quarter. Source: FRED.

TERM_t: Term premium is 10-year T-bond yield minus the 3-month T-bill rate. Source: FRED.

$\Delta\mathrm{TB}_t$: 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. Source: FRED.

DIV_t: Dividend yield is the cumulative dividend yield for the CRSP value-weighted stock portfolio in quarter t. Source: CRSP.

RET_t: Excess market return, cumulative quarterly return of the value-weighted CRSP market index minus the 3-month T-bill rate. Source: CRSP.

INF_t: Inflation is the quarterly change in Consumer Price Index (CPI) ending in months in quarter t. Source: WRDS.

ILLIQ_t: Illiquidity is the equal-weighted mean across stocks of daily average absolute return over dollar volume calculated for each NYSE stock. Source: CRSP.

4F-AIV_t: *4F-AIV* for stock j in quarter t is the residual sum of squares from Carhart's 4-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. Source: CRSP; Kenneth French's website.

4F-ASV_t: 4F-ASV for stock j in quarter t is the model sum of squares from the regression used to define 4F-$\mathrm{AIV}_{j,t}$. Market-wide 4F-ASV in quarter t is the value-weighted average ASV across all common stocks. Source: CRSP, Ken French's website.

C-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. Source: CRSP.

C-APV$_t$: C-APV for industry i in quarter t is return variation of industry j relative to the market return, $\sum_{s\in t}(R_{i,s}-R_{m,s})^2$. Market-wide C-APV in quarter t is the value-weighted average across all industries in the quarter. Source: CRSP.

C-ASV$_t$: *C-ASV* in quarter t is the variation of daily market-index return over quarter t, $\sum_{s\in t}\left(R_{m,s}-\overline{R}_{m,t}\right)^2$. Source: 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. Source: Chicago Fed.

Δln(PAT$_t$): Log difference between the number of patent applications between quarter t and $t-1$, aggregated across all firms. Source: Noah Stoffman's website.

Δln(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. Source: Noah Stoffman's website.

ΔTFP$_t$: Business sector total factor productivity growth, that is, the change of output growth less the contribution of capital and labor from quarter $t-1$ to t. Source: San Francisco Fed.

ΔLP$_t$: Business sector labor productivity growth in quarter t. Source: San Francisco Fed.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001417.

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