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Time-varying stock return correlation, news shocks, and business cycles

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Non-technical summary

Research Question

The correlation across returns on U.S. common stocks has varied substantially over the past few decades. Changes in stock return correlation affect investor welfare by changing the trade-off between risk and expected return: An increase in correlation implies a higher level of risk for equity portfolios, resulting in reduced gains from portfolio diversification. An increase in correlation does not only lead to lower diversification benefits, but it also reveals higher risk on the aggregate wealth portfolio that contains non-stock assets and that is not directly observable. This raises the question whether changes in return correlation are informative about business cycle fluctuations.

Contribution

The relationship between equity returns and economic activity has received considerable interest in both finance and macroeconomics. The macroeconomic literature has explored the link between economic conditions and stock market *volatility*. Our results provide a new angle on the relationship between equity returns and economic activity. Building on the insight from literature that changes in aggregate risk reveal themselves also through changes in the correlation between stock returns, we are the first to explore the informational content of changes in return correlation about business cycles.

Results

We find that an increase in the average correlation between U.S. industry returns is associated with lower future real GDP growth at a horizon of one to four years, and this relationship is highly statistically significant. The predictive power of return correlation is on a par with the slope of the yield curve and significantly exceeds that of some other widely used financial indicators. Innovations to return correlation affect macroeconomic aggregates in a vector autoregression (VAR). We find that a surprise increase in return correlation is followed by a persistent drop in output and a rise in prices. These dynamics are reminiscent of a negative aggregate supply shock. Innovations to return correlation bear a striking similarity to news shocks about total factor productivity (TFP), suggesting that market-wide changes in stock return correlation contain information about changes in future TFP.

Nichttechnische Zusammenfassung

Forschungsfrage

Die Korrelation zwischen den Renditen US-amerikanischer Aktien hat in den letzten Jahrzehnten stark fluktuiert. Veränderungen der Korrelation zwischen Aktienrenditen haben Auswirkungen auf Anleger, indem sie den Trade-off zwischen Risiko und erwarteter Rendite verändern: Eine Zunahme der Korrelation impliziert ein höheres Risiko für Aktienportfolios, was den Nutzen von Portfoliodiversifikation reduziert. Eine Zunahme der Korrelation führt nicht nur zu geringeren Diversifikationsvorteilen, sondern zeigt auch ein höheres aggregiertes Risiko an. Dies wirft die Frage auf, ob Veränderungen der Renditekorrelation Informationen über den Konjunkturverlauf beinhalten.

Beitrag

Sowohl in der Finanzwissenschaft als auch in der Makroökonomie ist der Zusammenhang zwischen Aktienerträgen und der Konjunktur ein wichtiges Thema. Die Verbindung zwischen Wirtschaftslage und der *Volatilität* der Aktienmarktrenditen wurde in der makroökonomischen Literatur untersucht. Unsere Ergebnisse liefern einen neuen Blickwinkel auf den Zusammenhang zwischen Aktienrenditen und wirtschaftlicher Aktivität. Aufbauend auf den Erkenntnissen aus der Literatur, dass sich Veränderungen des aggregierten Risikos auch in Veränderungen der Korrelation zwischen den Aktienrenditen zeigen, sind wir die Ersten, die den informativen Gehalt von Veränderungen der Aktienrenditekorrelation für den Konjunkturzyklen untersuchen.

Ergebnisse

Unsere Ergebnisse zeigen, dass ein Anstieg der durchschnittlichen Korrelation zwischen US-amerikanischen Aktienrenditen mit einem geringeren zukünftigen Wirtschaftswachstum in einem Zeitraum von einem bis vier Jahren einhergeht. Die Vorhersagekraft der Renditekorrelation entspricht jener der Zinsstrukturkurve und übertrifft die einiger anderer häufig verwendeter Finanzindikatoren. Unerwartete Veränderungen der Korrelation zwischen den Aktienrenditen beeinflussen makroökonomische Aggregate in einer Vektorautoregression. Einem überraschenden Anstieg der Renditekorrelation folgt ein langanhaltender Produktionsrückgang und ein Preisanstieg. Diese Dynamik ähnelt einem negativen gesamtwirtschaftlichen Angebotsschock. Schocks auf die Korrelation der Renditen weisen eine auffällige Ähnlichkeit mit Schocks über zukünftige Faktorproduktivität auf. Dies deutet darauf hin, dass marktweite Veränderungen der Korrelation der Aktienrenditen Informationen über Änderungen der künftigen Wirtschaftsproduktivität enthalten.

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Abstract

The cross-sectional average of pairwise correlations across stocks traded on the NYSE, AMEX, and Nasdaq is a powerful predictor of U.S. economic activity at a horizon of one to four years. Its predictive ability is on a par with the slope of the yield curve and significantly exceeds that of some other widely used financial indicators. The macroeconomic effects of an innovation to stock return correlation in a vector autoregression are nearly identical to those of a news shock about future productivity. Thus, market-wide changes in return correlation contain information about changes in future technological developments.

JEL classification: E32, E44

Keywords: Business Cycles, News Shock, Stock Market, Uncertainty

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1 Introduction

The correlation across returns on U.S. common stocks displays substantial time variation (Campbell et al., 2001). This variation appears to be counter-cyclical. For instance, the average pairwise correlation between industry returns on stocks traded on the NYSE, AMEX, and Nasdaq is negatively related to U.S. real GDP growth (with a correlation of -0.30 over the 1964-2021 period), and it rose ahead of virtually every recession over the past six decades (see Figure 1). Stock return correlation reached a historical high of 0.83 shortly after the bankruptcy of Lehman Brothers in 2008 from below 0.20 at the beginning of the new millennium. It then decreased after the financial crisis, before surging again to above 0.80 during the COVID-19 recession. Against this background, the question arises whether changes in return correlation are informative about business cycle fluctuations.

In this paper, we study the relationship between business fluctuations and changes in stock return correlation. To preview our results, we find using predictive regressions that an increase in the average correlation between U.S. industry returns is associated with lower future real GDP growth at a horizon of one to four years, and this relationship is highly statistically significant. The predictive power of return correlation is on a par with the slope of the yield curve and significantly exceeds that of some other widely used financial indicators, such as the Gilchrist and Zakrajsek (2012) credit spread. In addition, we study how innovations to return correlation affect macroeconomic aggregates in a structural vector autoregression (VAR). A surprise increase in return correlation is followed by a persistent drop in output and a rise in prices. These dynamics are reminiscent of a negative aggregate supply shock. Innovations to return correlation bear a striking similarity to news shocks about total factor productivity (TFP), suggesting that market-wide changes in stock return correlation contain information about changes in future TFP. This finding rationalizes the negative supply effects.

Our investigation starts with a decomposition of stock market volatility borrowed

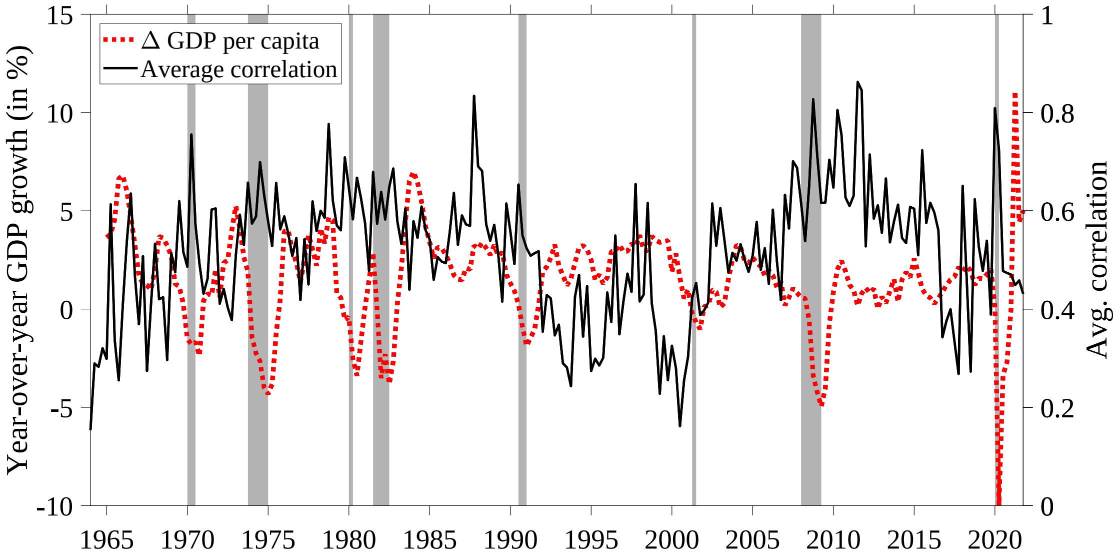


Figure 1: **Average correlation between returns on U.S. industry portfolios**

Notes: The black solid line is the cross-sectional average correlation between value-weighted returns on NYSE, AMEX, and Nasdaq stocks sorted into 49 Fama-French industry portfolios, calculated according to Equation (9) (measured on the right axis). The red dotted line is the year-over-year growth rate of U.S. real GDP per capita (measured on the left axis). The shaded regions represent eight recession periods dated by the National Bureau of Economic Research (NBER). Sample: 1964Q1-2021Q4.

from the asset pricing literature. A simple portfolio-theoretic framework allows us to decompose the variance of the market return into the product of two well-defined objects: (1.) the cross-sectional average variance of individual stock returns (henceforth AV) and (2.) cross-sectional average correlation (henceforth AC) (see Driessen et al., 2009; Pollet and Wilson, 2010). These two components capture almost all of the time-series variation in post-war U.S. stock market variance (see Pollet and Wilson, 2010). Using this decomposition as our guiding framework, we study the macroeconomic implications of changes in AV and AC, both from a reduced-form perspective and within a structural VAR framework.

Our analysis is structured as follows. First, we document the time series behavior of AV and AC in a sample that covers over half a century of U.S. data. To that end, we compute the realized variances of daily value-weighted returns on NYSE, AMEX, and Nasdaq stocks sorted into 49 Fama and French (1997) industry portfolios and the realized correlations for all pairs of industry portfolios between 1964Q1 and 2021Q4. We calculate AV as the cross-sectional mean of the realized variances and AC as the cross-sectional mean of the realized correlations. Using OLS regressions, we corroborate the main empirical results of Pollet and Wilson (2010) on our sample. On the one hand, we show that the product of AV and AC provides a good approximation of aggregate stock market variance. On the other hand, while AV more accurately predicts subsequent market variance than AC, it has no discernible forecasting power for excess stock market returns. AC instead strongly predicts future excess returns.

Next, we explore the predictive content of AV and AC for economic activity. This exercise closely follows Gilchrist and Zakrajsek (2012), who document that a credit spread index built from a broad range of U.S. corporate bonds has superior forecasting power for U.S. economic activity over the Treasury term spread and the federal funds rate. We find that both AV and AC are statistically significant predictors of economic activity, and that they are negatively associated with future GDP growth. However, while AV and the Gilchrist and Zakrajsek (2012) credit spread quickly lose their forecasting power over time, AC emerges as a powerful predictor that is matched only by the term spread at longer forecast horizons of two to four years. This finding is new to the literature and constitutes our first main contribution.

Having established the forecasting power of AV and AC for economic growth, we then study how innovations to AV and AC affect macroeconomic variables in a VAR. We find that an unexpected increase in AV leads to a rapid drop and recovery in consumption, investment, output, and hours, and to a persistent decrease in the price level. These effects resemble a negative aggregate demand shock. The effects reach their maximum at two to four quarters after the shock and die out beyond the two-year horizon. These dynamics are consistent with the sharp contraction and recovery in economic activity observed after an uncertainty shock identified from movements in stock market volatility (e.g., Bloom, 2009). An unexpected increase in AC has similar but more long-lasting macroeconomic effects. Consumption, investment, and output all decrease on impact.

The response of consumption is close to a permanent reduction, while investment, output, and hours display relatively persistent, hump-shaped responses. A distinguishing feature of an AC shock is that it leads to an *increase* in the price level. It is thus reminiscent of a negative aggregate supply shock.

Finally, in order to better understand what an "AC shock" might actually capture, we compare the time series of AC innovations estimated from the VAR with more conventional structural shocks. AC shocks bear little resemblance to fiscal, monetary, or trade policy shocks. They are also unrelated to surprise technology shocks. Instead the data point to financial shocks and TFP news shocks as two potential sources of AC innovations.[1] The impulse responses implied by these shocks allow us to discriminate between the two alternatives. The reaction of output together with the inverse reaction of prices after an AC shock rule out the financial shock interpretation. By contrast, our second main contribution is to show that the macroeconomic effects of an AC shock are nearly identical to those of a TFP news shock, which explains the negative supply effects.

There is a growing literature linking time-varying return correlation to aggregate fluctuations. Changes in stock return correlation affect investor welfare by changing the trade-off between risk and expected return (Markowitz, 1952). In addition, changes in return correlation might also be relevant from a macroeconomic perspective. In particular, motivated by the Roll (1977) critique, Pollet and Wilson (2010) show that changes in stock return correlation predict excess returns because they reveal changes in the risk on the unobservable portfolio of aggregate wealth (see also Krishnan et al., 2009; Driessen et al., 2009).[2] Changes in stock return correlation may thus signal changes in aggregate risk in the economy. Moreover, using a general equilibrium asset pricing model with heterogeneous risk aversion, Ehling and Heyerdahl-Larsen (2017) show that stock return correlation varies counter-cyclically with the business cycle. In the model, consumption

[1]We measure financial shocks using the excess bond premium proposed by Gilchrist and Zakrajsek (2012). Our measure of TFP news shocks comes from Beaudry and Portier (2006).

[2]In seminal work, Roll (1977) criticizes empirical tests of the capital asset pricing model (CAPM) on the grounds that the true portfolio of aggregate wealth is not observable, and the stock market portfolio is only a subset of aggregate wealth. This inhibits empirically studying the relationship between the excess return on aggregate wealth and the variance of this return (i.e., the risk on aggregate wealth).

risk sharing between heterogeneous consumers with constant relative risk aversion causes cyclical variations in the volatility of aggregate risk aversion and, in turn, leads to cyclical variation in return correlation. The model quantitatively matches average industry return correlations and changes in correlations from business cycle peaks to troughs in U.S. data.

From a broader perspective, the relationship between equity returns and economic activity has received considerable interest in both finance and macroeconomics. Financial economists have paid particular attention to the observation that expected excess returns on stocks vary with business cycle conditions so that equity premia are high during downturns (e.g., Fama and French, 1989; Campbell and Cochrane, 1999; Lettau and Ludvigson, 2001; Campbell and Diebold, 2009). Macroeconomists have built on this insight by exploiting movements in stock prices to study the role of expectations in business cycle fluctuations (e.g., Beaudry and Portier, 2004, 2006). In a seminal paper, Beaudry and Portier (2006) show that news about future TFP – which are instantaneously priced in the stock market but have no contemporaneous impact on TFP – are responsible for an important fraction of business cycle fluctuations. The question whether news drive business cycles has subsequently attracted considerable attention (for an overview, see Beaudry and Portier, 2014).

In addition, a great amount of macroeconomic literature has explored the link between economic conditions and stock market *volatility*. The time series evidence points to a counter-cyclical relationship (e.g., Schwert, 1989; Hamilton and Lin, 1996; Engle and Rangel, 2008; Conrad and Loch, 2015). Unexpected increases in stock market volatility have been attributed to uncertainty shocks that lead to a rapid drop and rebound in economic activity (e.g., Bloom, 2009; Bekaert et al., 2013; Caggiano et al., 2014; Leduc and Liu, 2016; Caldara et al., 2016; Basu and Bundick, 2017; Ludvigson et al., 2021). Using a structural model of firm production behavior, Bloom (2009) shows that firms become more cautious and scale back their hiring and investment rates in the period immediately after an uncertainty shock, generating a decline in aggregate production. Once uncertainty subsides, hiring and investment activity quickly bounces back, and a volatility overshoot occurs. Stock market volatility is the preferred measure of uncertainty in most of this literature, although some papers use news articles, surveys, econometric or structural models to measure uncertainty (see Berger et al., 2019; Cascaldi-Garcia et al., forthcoming; David and Veronesi, forthcoming). Moreover, what seems to matter for economic growth is aggregate uncertainty rather than firm-level cross-sectional uncertainty (Dew-Becker and Giglio, forthcoming).

Our results provide a new angle on the relationship between equity returns and economic activity. Building on the insight from Pollet and Wilson (2010) that changes in aggregate risk reveal themselves through changes in the correlation between stock returns, we are the first to show that changes in return correlation also contain information about business cycles. Specifically, we document that return correlation is a powerful predictor of GDP growth at business cycle frequencies. We further show that shocks to return correlation resemble supply-side shocks and co-vary strongly with news shocks about future technological developments. This finding suggests that TFP news shocks are the key source of aggregate risk priced in excess stock market returns.

The rest of the paper is organized as follows. We decompose stock market variance into AV and AC in Section 2. In Section 3, we investigate their predictive ability for GDP growth, and we study the macroeconomic effects of AV and AC shocks. Section 4 concludes.

2 Stock market variance and its components

2.1 An approximation for stock market variance

Let m denote the value-weighted market portfolio which consists of N stocks (N is large), where $w_{i,t}$ is the weight of stock i in the market at time t. The variance of the return on the market portfolio is:

$$\sigma_{m,t}^2 = \sum_{i=1}^{N} w_{i,t}^2 \sigma_{i,t}^2 + \sum_{i=1}^{N} \sum_{j \neq i} w_{i,t} w_{j,t} \sigma_{i,t} \sigma_{j,t} \rho_{i,j,t}, \tag{1}$$

with time-varying individual standard deviations $\sigma_{i,t}$ and time-varying pairwise correlations $\rho_{i,j,t}$. Stock market variance $\sigma_{m,t}^2$ can be approximated by the product of two terms (see Driessen et al., 2009; Pollet and Wilson, 2010):

$$\sigma_{m,t}^2 \approx \bar{\sigma}_t^2 \bar{\rho}_t. \tag{2}$$

The first term on the right-hand-side of Equation (2) is the weighted cross-sectional average variance for the N stocks:

$$\bar{\sigma}_t^2 = \sum_{i=1}^{N} w_{i,t} \sigma_{i,t}^2, \tag{3}$$

and the second term on the right-hand-side of Equation (2) is the weighted cross-sectional average correlation between all pairs of stocks:

$$\bar{\rho}_t = \sum_{i=1}^{N} \sum_{j \neq i} w_{i,t} w_{j,t} \rho_{i,j,t}. \tag{4}$$

Equation (2) provides a good approximation as long as stock-specific deviations from average variance are small (see Appendix A for details).

Our primary objective is to study the relationship between time-varying stock return correlation and macroeconomic conditions. Thus, the decomposition in Equation (2), which provides two well-defined objects – average variance and average correlation – will be the starting point of our analysis. It seems intuitive that the variation in individual stock returns should be reflected in the variance of the market portfolio. However, it is perhaps less widely appreciated that the time-varying correlation between stock returns is also an important source of market variance. Moreover, Pollet and Wilson (2010) show that changes in average variance of individual stocks do not carry a positive price of risk in the stock market. By contrast, they show that changes in stock return correlation are priced in excess stock market returns because they reveal changes in the risk on aggregate wealth.

2.2 Data and measurement

We estimate stock market variance, average variance, and average correlation at the quarterly frequency, using daily value-weighted returns on NYSE, AMEX, and Nasdaq stocks sorted into 49 Fama-French industry portfolios (Appendix D provides variable sources and definitions). We use Fama-French industry portfolios because they are representative for the near-universe of stocks traded on the U.S. stock market, and the data are freely available in a standardized way at a daily frequency for a period stretching back several decades, which increases the reproducibility of our results. When using Fama-French industry portfolios weighted equally across industries, Pollet and Wilson (2010) find results similar to those obtained using individual equity returns. We also corroborate their main empirical results on our sample.

Our data span the period 1964Q1-2021Q4. We compute the realized variance of industry portfolio $i = 1, \ldots, N$ in quarter $t = 1, \ldots, T$ as

$$RV_{i,t}^{Q} = \sum_{j=1}^{Q_t} r_{j,i,t}^2, \tag{5}$$

where there are Q_t daily returns $r_{j,i,t}$ in quarter t (see Schwert, 1989). Under suitable conditions, $RV_{i,t}^{Q}$ is an unbiased and efficient estimator of return variance (see Andersen et al., 2001, 2003). The realized covariance between the return on portfolio i and k ($k \neq i$) in quarter t is

$$RCOV_{i,k,t}^{Q} = \sum_{j=1}^{Q_t} r_{j,i,t} r_{j,k,t}. \tag{6}$$

We use the realized variances and covariances to estimate quarterly market variance

(MV_t), average variance (AV_t), and average correlation (AC_t), using equal weights as Pollet and Wilson (2010) do for industry portfolios. In particular, we calculate MV_t from the realized variances and covariances of the $N = 49$ industry portfolios using Equation (1) as follows:

$$MV_t = \frac{1}{N^2} \sum_{i=1}^{N} RV_{i,t}^{Q} + \frac{1}{N^2} \sum_{i=1}^{N} \sum_{k \neq i} RCOV_{i,k,t}^{Q}. \tag{7}$$

Moreover, we compute AV_t by taking the arithmetic cross-sectional mean of $RV_{i,t}^{Q}$ across the 49 industry portfolios:

$$AV_t = \frac{1}{N} \sum_{i=1}^{N} RV_{i,t}^{Q}. \tag{8}$$

Finally, we obtain AC_t as the arithmetic cross-sectional mean of the pairwise realized correlation of daily returns during each quarter for all 1176 pairs of industry portfolios:

$$AC_t = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{k \neq i} \frac{RCOV_{i,k,t}^{Q}}{\sqrt{RV_{i,t}^{Q} RV_{k,t}^{Q}}}. \tag{9}$$

2.3 The relationship between market variance and its two components

Figure 2 presents the time profile of AV_t and AC_t together with stock market variance, MV_t. The shaded regions represent recession periods dated by the National Bureau of Economic Research (NBER), and the vertical red lines denote 16 dates that represent historical events selected by Bloom (2009) to construct his benchmark measure of exogenous "uncertainty shocks", which we complement by the COVID-19 recession.[3] There is a large degree of co-movement between stock market variance and average variance: the sample correlation between MV_t and AV_t is equal to 0.97. The correlation between MV_t

[3] The events selected by Bloom (2009) are: the escalation of the Vietnam War (1966Q3); the military campaign in Cambodia and shootings at Kent State University (1970Q2); the first OPEC oil crisis and the Arab-Israeli War (1973Q4); the collapse of Franklin National Bank (1974Q4); the second OPEC oil crisis (1978Q4); the beginning of the Soviet-Afghan War and Iran hostage crisis (1980Q1); the monetary cycle turning point (1982Q4); the Black Monday on world stock markets (1987Q4); the first Gulf War (1990Q4); the East Asian financial crisis (1997Q4); the Russian crisis and LTCM default (1998Q3); the 9/11 terrorist attack (2001Q3); the dot-com crash and Enron bankruptcy (2002Q3); the second Gulf War (2003Q1); and the credit crunch and global financial crisis (2008Q4).

and AC_t is also positive, albeit somewhat lower, at 0.48. The two components of market variance, AV_t and AC_t, are also positively correlated with a correlation coefficient equal to 0.38. Both series display peaks on Bloom's dates and during the COVID-19 recession. Spikes in stock market volatility thus reflect a combination of, on average, higher individual stock return variances and higher correlations.

We replicate a set of predictive regressions for stock market variance and excess returns by Pollet and Wilson (2010), using AC_t and AV_t as predictors. While the sample of Pollet and Wilson (2010) ends in 2006Q4, our data span fifteen more years, thus making it worthwhile to revisit this issue. Our estimates corroborate their main results. In particular, we find that the product of AV and AC provides a good approximation of stock market variance (see the top panel of Table A.1 in Appendix B).[4] Individually, AV explains a larger amount of the variation in contemporaneous market variance than AC, and it also more accurately predicts subsequent market variance (see the bottom panel of Table A.1 in Appendix B). More importantly, we show that AC strongly predicts future excess stock market returns, while AV has no discernible forecasting power for excess returns (see Table A.2 in Appendix B).

3 Macroeconomic implications

3.1 The predictive content of AV and AC for economic activity

Given the differential performance of AV_t and AC_t in forecasting market variance and excess returns, we now turn to analyzing their predictive ability for economic activity. We employ univariate (in-sample) predictive regressions that closely follow Gilchrist and Zakrajsek (2012). Their econometric model takes the following form:

$$\Delta_h GDP_{t+h} = \alpha + \sum_{i=1}^{l} \beta_i \Delta GDP_{t-i} + \gamma_1 TS_t + \gamma_2 RFF_t + \gamma_3 GZ_t + \epsilon_{t+h}, \qquad (10)$$

[4]In addition, Figure A.1 in Appendix C visually illustrates that MV_t can be well approximated by the product of AV_t and AC_t with an approximation error close to zero.

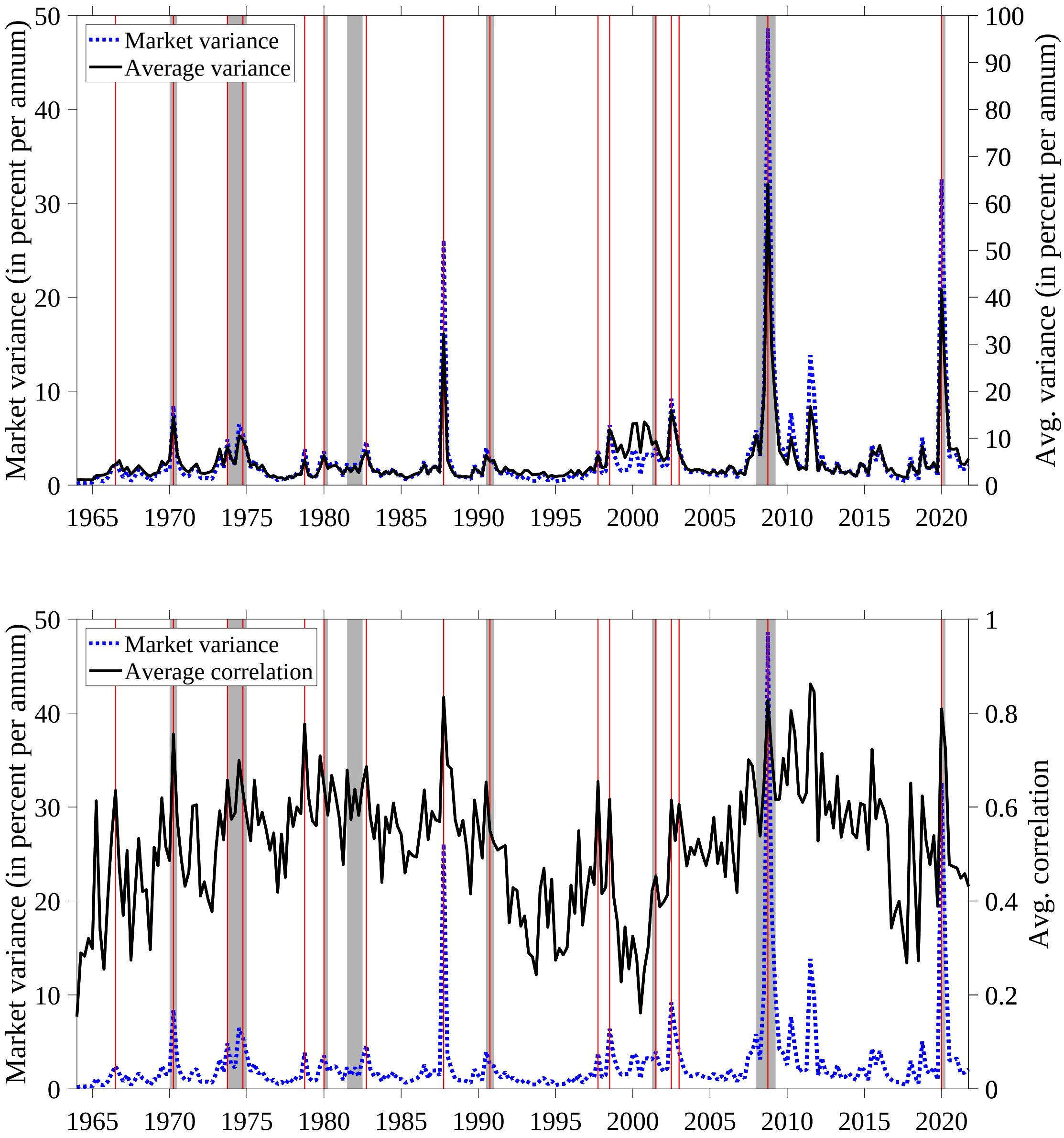


Figure 2: **Stock market variance and its components**

Notes: Top panel: Market variance (measured on the left axis) and average variance (measured on the right axis). Bottom panel: Market variance (measured on the left axis) and average correlation (measured on the right axis). Market variance is calculated from quarterly realized variances and covariances of daily returns on 49 Fama-French industry portfolios using Equation (7). Average variance is the cross-sectional average of the quarterly realized variances of 49 industry portfolios (see Equation (8)). Average correlation is the cross-sectional average of the realized correlations for all 1176 pairs of industry portfolios (see Equation (9)). The shaded regions represent NBER recession dates. The vertical red lines denote 16 major historical events dated by Bloom (2009) and the COVID-19 recession (see the main text for details). Sample: 1964Q1-2021Q4.

where $\Delta_h GDP_{t+h}$ denotes the h-quarters-ahead percentage change in U.S. log real GDP ($\Delta_h GDP_{t+h} \equiv \frac{400}{h+1} \ln \frac{GDP_{t+h}}{GDP_{t-1}}$). The latter is regressed on a constant α, past values of GDP growth ($\Delta GDP_{t-i} \equiv GDP_{t-i} - GDP_{t-i-1}$ with $i = 1, \ldots, l$), and a set of financial predictors that includes the U.S. Treasury term spread TS_t, the real federal funds rate RFF_t, and the Gilchrist-Zakrajsek credit spread index GZ_t (henceforth GZ spread). Appendix D provides data definitions and sources. We complement the set of financial predictors in Equation (10) by AV_t and AC_t.[5] Table 1 reports the sample correlation between the five regressors, indicating that AV_t and AC_t are positively associated with the GZ spread, and weakly negatively associated with the other two financial predictors.

We estimate Equation (10) using OLS and choose the lag length l for the autoregressive terms in each specification optimally using the Akaike information criterion (AIC). The sample period begins in 1973Q1 due to availability of the GZ spread. It ends in 2019Q4 because the COVID-19 recession has been argued to severely distort macroeconometric model estimates and forecasts (e.g., Schorfheide and Song, 2021; Lenza and Primiceri, 2022). We conduct a robustness check with data until 2021Q4. Since we are primarily interested in business cycle dynamics rather than near-term forecasting performance, we generate forecasts at a horizon of one to four years ($h \in \{4, 8, 12, 16\}$ quarters). The forecast error ϵ_{t+h} follows an MA(h-1) process under the null hypothesis of no predictability because of overlapping observations. To account for the overlap in the residuals for $h \geq 1$, and to capture potential heteroskedasticity, we compute Hodrick (1992) 1B standard errors.[6]

Table 2 shows the results for the predictive regressions. The slope of the yield curve significantly predicts GDP growth at all horizons and along all different model specifications, consistent with earlier studies (e.g., Estrella and Mishkin, 1998). The real federal funds rate has some forecasting ability at a horizon of three and four years but has less

[5]We apply the Fisher Z-transformation to AC_t in order to use a variable in the predictive regressions that is approximately normally distributed. Predictive regressions with the non-transformed variable yield nearly identical results.

[6]Ang and Bekaert (2007) show that Hodrick (1992) 1B standard error estimates retain the correct size in small samples while other heteroskedasticity and autocorrelation consistent (HAC) estimators severely over-reject the null hypothesis of no predictability.

	RFF_t	GZ_t	AV_t	AC_t
TS_t	0.52***	-0.19***	-0.14**	-0.12*
RFF_t		-0.37***	-0.12*	-0.08
GZ_t			0.66***	0.22***
AV_t				0.54***

Table 1: Correlations matrix of financial predictors

Notes: This table shows the pairwise correlation coefficients between the financial predictor variables for the longest available sample. TS_t is the U.S. Treasury term spread, RFF_t is the real federal funds rate, GZ_t is the GZ spread, AV_t is the cross-sectional average variance of returns on 49 Fama-French industry portfolios, and AC_t is the Fisher Z-transformed cross-sectional average correlation of returns on 49 Fama-French industry portfolios. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

predictive power at shorter horizons. On the contrary, the GZ spread is a good predictor of GDP growth at the one-year horizon, in line with Gilchrist and Zakrajsek (2012). The parameter estimate on the GZ spread is statistically significant at the 1% level, and the adjusted R^2 increases by 13 percentage points (p.p.) from 0.18 to 0.31 when adding the GZ spread to the regression (see columns (1) and (2) in panel (a)). However, its predictive power deteriorates quickly for longer horizons: The parameter estimates on the GZ spread are only marginally significant at the two-year horizon and turn insignificant at the three-year and four-year horizon (see panels (b) and (d)).

When individually included, both AV_t and AC_t have statistically significant predictive power for economic activity at all four horizons, and they are both negatively associated with future GDP growth. However, AC_t clearly emerges as the better predictor at longer horizons. Specifically, at the four-year horizon, the parameter estimate on AC_t is statistically significant at the 1% level and the adjusted R^2 increases by nine p.p. to 0.50 when adding it to the model specification (see column (4) in panel (d)). By contrast, it only increases by three p.p. when including AV_t into the specification (see column (3) in panel (d)). In the joint model specification, AV_t has a marginal predictive content for GDP growth only at the one-year horizon, but the sign switches from negative to positive (see column (5) in panel (a)). By contrast, an increase in AC_t robustly predicts a decrease in future GDP growth at a horizon of one to four years, with a coefficient estimate that is always statistically significant at least at the 5% confidence level (see column (4) in panel (a) to (d)). Moreover, the information contained in AC_t is statistically relevant for future GDP growth at all four horizons, even when controlling for the other predictors (see column (5) in panel (a) to (d)).

We obtain nearly identical results when replacing AV_t with MV_t in the regressions (see Table A.3 in Appendix C). The results are also robust to including the COVID-19 recession into the sample, although the coefficients on AC_t are statistically significant only at the 10% level in the joint specification at the two-year horizon and in both specifications at the three-year horizon (see Table A.4 in Appendix C). We thus conclude that, while AV_t and AC_t both predict GDP growth one year ahead, AC_t is an excellent predictor at a forecast horizon of one to four years.

3.2 VAR model

Having established the forecasting power of AV and AC for GDP growth in a reduced-form setup, we now turn to analyzing the economic mechanisms that relate AV and AC to economic activity within a structural VAR framework. We estimate the macroeconomic effects of shocks to AV_t and AC_t in an otherwise standard VAR model for the U.S. economy.

Specifically, let y_t denote an $n \times 1$ vector of endogenous variables observed in period $t = 1, \ldots, T$. Consider the following VAR(p) in reduced form:

$$y_t = \mu + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t, \tag{11}$$

where μ is an $n \times 1$ vector of constants, B_i are $n \times n$ coefficient matrices for $i = 1, ..., p$, where p denotes the lag order, and u_t is an $n \times 1$ vector of reduced-form errors with $n \times n$ variance-covariance matrix $\Sigma_u = E[u_t, u_t']$. The VAR includes the following endogenous variables for the U.S. economy: AC_t; AV_t; the log of real GDP; the log of real consumption; the log of real investment; the log of hours worked; the log of the price level; and the

	Dependent variable: $\Delta_h GDP_{t+h}$									
	(a) h=4 quarters					(b) h=8 quarters				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
TS_t	-0.41	-0.41	-0.42	-0.42	-0.41	-0.63	-0.62	-0.64	-0.64	-0.62
	[3.67]	[3.67]	[3.75]	[3.71]	[3.57]	[4.34]	[4.46]	[4.58]	[4.36]	[4.26]
RFF_t	0.17	0.01	0.15	0.15	-0.05	0.36	0.23	0.34	0.34	0.19
	[1.27]	[0.04]	[1.14]	[1.16]	[0.36]	[2.24]	[1.38]	[2.18]	[2.13]	[0.98]
GZ_t		-0.43			-0.59		-0.31			-0.42
		[3.63]			[3.32]		[2.14]			[1.72]
AV_t			-0.24		0.23			-0.19		0.17
			[3.93]		[2.08]			[2.98]		[1.19]
AC_t				-0.19	-0.20				-0.23	-0.24
				[2.20]	[2.07]				[2.14]	[2.02]
Adj. R^2	0.18	0.31	0.23	0.21	0.34	0.31	0.38	0.34	0.36	0.42
	(c) h=12 quarters					(d) h=16 quarters				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
TS_t	-0.69	-0.68	-0.70	-0.69	-0.67	-0.70	-0.68	-0.70	-0.69	-0.67
	[4.07]	[4.25]	[4.34]	[4.10]	[3.97]	[3.67]	[3.78]	[3.85]	[3.67]	[3.48]
RFF_t	0.53	0.43	0.51	0.50	0.41	0.68	0.59	0.65	0.66	0.53
	[2.83]	[2.00]	[2.74]	[2.64]	[1.62]	[3.32]	[2.42]	[3.21]	[3.20]	[1.87]
GZ_t		-0.23			-0.28		-0.27			-0.35
		[1.19]			[0.84]		[1.23]			[0.92]
AV_t			-0.19		0.07			-0.19		0.14
			[2.59]		[0.40]			[2.65]		[0.65]
AC_t				-0.28	-0.28				-0.33	-0.34
				[2.35]	[2.30]				[2.61]	[2.56]
Adj. R^2	0.36	0.39	0.39	0.43	0.46	0.41	0.45	0.44	0.50	0.54

Table 2: Financial predictors of economic activity, 1973Q1-2019Q4

Notes: This table reports results from a predictive regression of U.S. real GDP growth h quarters into the future, $\Delta_h GDP_{t+h}$, on financial predictors. Panels (a) to (d) contain the results for forecast horizons of $h \in \{4, 8, 12, 16\}$ quarters. Column (1) reports estimates from a specification that includes the term spread, TS_t, and the real federal funds rate, RFF_t. Columns (2) to (4) report estimates that additionally include the Gilchrist and Zakrajsek (2012) credit spread, GZ_t, the cross-sectional average variance of returns on 49 Fama-French industry portfolios, AV_t, and the (Fisher Z-transformed) cross-sectional average correlation of returns on 49 Fama-French industry portfolios, AC_t, one at a time. Column (5) reports estimates from a specification that simultaneously includes all five financial variables. Each specification also includes a constant and p lags of GDP growth (not reported), where p is determined by the AIC. Entries in the table denote the standardized estimates of the OLS coefficients. Absolute asymptotic t-statistics computed based on Hodrick (1992) 1B standard errors are reported in square-brackets. In-sample goodness of fit is measured by the adjusted R^2.

one-year Treasury yield (Appendix D provides details on the data used in the analysis). The choice of variables in the VAR closely follows the recent literature that uses stock market volatility as a proxy for uncertainty. Specifically, it is nearly identical to the model specification in Basu and Bundick (2017), except that we replace market volatility by its two components. A standard approach to identify uncertainty shocks in the related literature consists of assuming that stock market volatility has contemporaneous effects on all endogenous variables in a recursive VAR (e.g., Bloom, 2009; Leduc and Liu, 2016; Basu and Bundick, 2017). In line with this approach, we recover orthogonal innovations to AC_t and AV_t by applying a Cholesky decomposition to Σ_u. Our recursive ordering places AC_t first and AV_t second, followed by all other variables. We reverse this order in a robustness check.

We estimate the VAR by OLS for the period 1964Q1-2019Q4, using p=2 lags as indicated by the AIC. We include the COVID-19 pandemic period in a robustness check. Residuals of a VAR model that spans more than half a century of financial and macroeconomic data are prone to conditional heteroskedasticity. To guard against this, we conduct inference using a residual-based moving block bootstrap proposed by Brüggemann et al. (2016), which produces asymptotically valid confidence intervals in the presence of conditional heteroskedasticity of unknown form. We set the block length in the bootstrap equal to the nearest integer of $5.03T^{1/4}$, as suggested by Jentsch and Lunsford (2019). Throughout the paper, we report 68% and 90% confidence intervals based on 5000 moving block bootstrap replications using the method of Hall (1992).

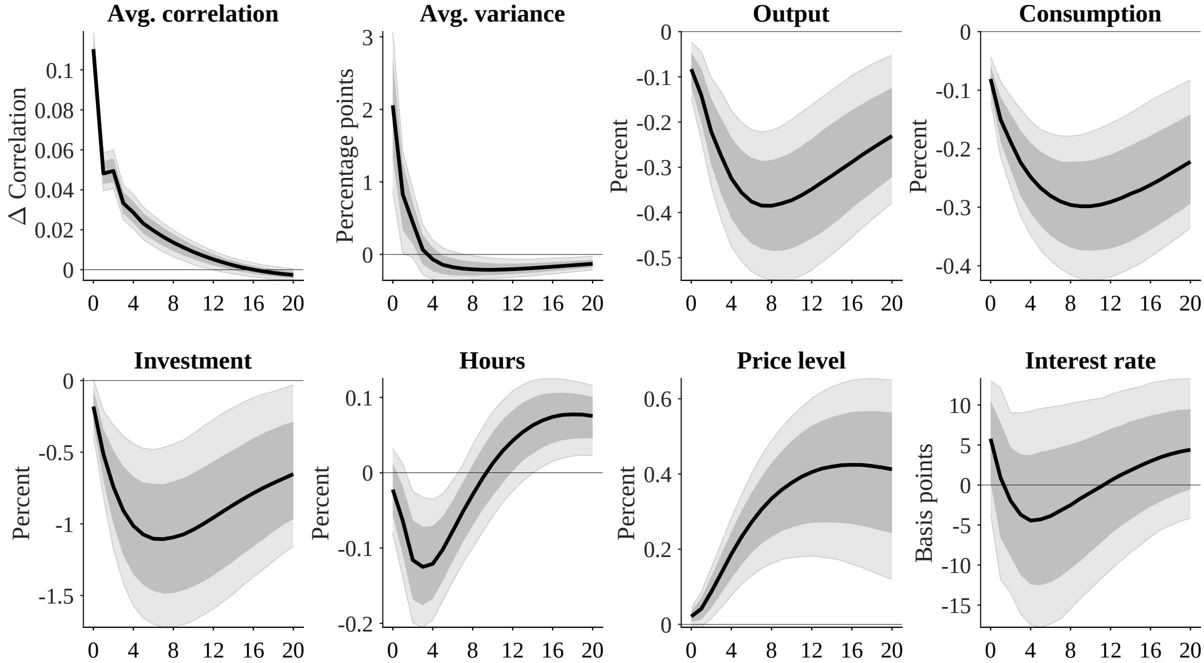
3.3 VAR estimates

Figure 3 shows the impulse responses of U.S. macroeconomic variables to a one-standard-deviation orthogonal increase in AC_t (top panel) and in AV_t (bottom panel). An AC shock raises AC_t on impact to 0.63 from its mean of 0.52, and AC_t returns to the baseline level after three years. The AC shock is followed by a statistically significant and long-lasting decrease in output, consumption, and investment. The persistent impulse response pattern is consistent with the results from the long-horizon predictive regressions. The output contraction reaches its trough after two years at nearly 0.40% below the baseline. Consumption drops by slightly less than output, while investment declines nearly three times as much as output. The AC shock also leads to a statistically significant and hump-shaped decrease in hours and to a persistent increase in the price level.

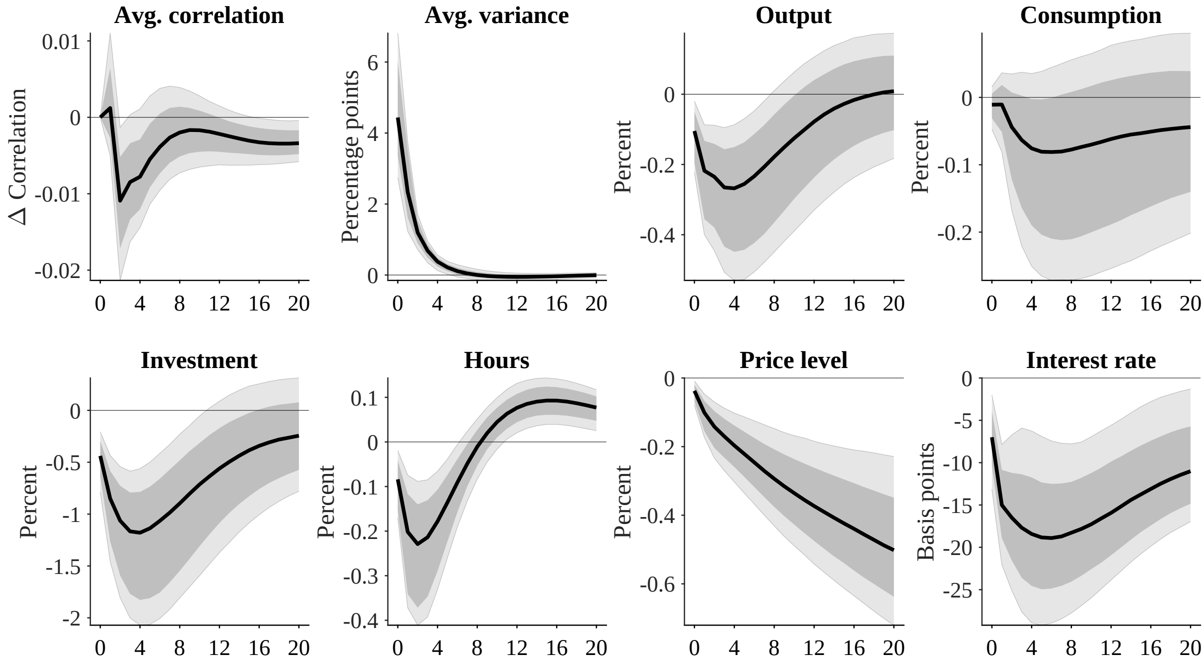
An AV shock of one standard deviation raises AV_t on impact by 4.46 p.p. from its mean of 4.86% per annum. The estimated effects are less persistent than those of an AC shock, reaching their maximum at about two to four quarters, consistent with the results from the forecasting exercise. Output significantly drops on impact and reaches its peak decrease of nearly 0.30% after one year. Consumption also tends to decrease, albeit its response is not statistically significant at the 10% level. The response of investment is more pronounced than that of output, with a peak drop of 1.20% at the one-year horizon. The AV shock leads to a significant decrease and subsequent rebound in hours. Finally, the price level and the short-term interest rate drop persistently after the shock.

3.4 Robustness

Figure A.2 in Appendix C shows the results from various robustness checks. First, we obtain very similar results when extending the sample up to 2021Q4. The inclusion of data observed during the COVID-19 pandemic into the sample leads to impulse responses that display a characteristic V-shape at the short end but are otherwise qualitatively identical to the baseline results (red dotted lines). The responses become much more similar to the baseline effects when we omit the observations in 2020Q1 and 2020Q2 from the sample but keep the observations thereafter, as suggested by Schorfheide and Song (2021) and Lenza and Primiceri (2022) (red dotted lines with circles). Second, the results are robust to reversing the recursive order with AV_t first and AC_t second, followed by all other variables (yellow stars). Third, our conclusions remain unchanged when using the GDP-deflator as a price measure (blue dashed lines), and when using the effective federal



(a) **Responses to an orthogonal increase in AC**



(b) **Responses to an orthogonal increase in AV**

Figure 3: **Effects of an orthogonal increase in AC and AV**

Notes: The figure depicts impulse responses to a one-standard-deviation positive shock to AC (top panel) and AV (bottom panel). The shaded areas represent 68% (dark gray) and 90% (light gray) confidence intervals based on 5000 moving block bootstrap replications using the method of Hall (1992). The x-axis shows quarters after the shock.

funds rate instead of the one-year Treasury yield.[7] Finally, our findings are robust to estimating the VAR with four lags (turquoise lines with diamonds).

3.5 Interpretation

The VAR estimates lead us to two conclusions. First, the macroeconomic dynamics following an orthogonal increase in AV are reminiscent of a negative aggregate *demand* shock, associated with a drop in output together with a *decrease* in prices. They also resemble the effects of an uncertainty shock identified through spikes in stock market volatility, which is not surprising given the strong positive correlation between AV_t and MV_t.[8] Leduc and Liu (2016) show that uncertainty shocks produce effects consistent with demand shocks. Taken together, this suggests that AV shocks are uncertainty shocks that affect the economy through a reduction in aggregate demand. Second and by contrast, an orthogonal rise in AC leads to a persistent *increase* in prices. Its effects thus bear resemblance to those of a negative aggregate *supply* shock, which implies that AC shocks operate through channels other than uncertainty. This begs the question of how to interpret orthogonal changes in average stock return correlation. We turn to this question in the remainder of the paper.

One way to gain insights into what an "AC shock" might actually capture is by studying the historical narrative implied by the time profile of the estimated shock series, depicted in Figure 4. The largest AC shocks occurred during some well known historical events, including the oil crises of the 1970s, the 1987 Black Monday stock market crash, the 1997 Asian crisis, the 1998 Russian crisis and LTCM default, the 2008 Lehman bankruptcy, the 2011 European debt crisis, and the 2018 stock market meltdown.[9] While

[7] Following Basu and Bundick (2017), we use the Wu and Xia (2016) shadow federal funds rate between 2009Q1 and 2015Q4 to account for the stance of monetary policy during the zero lower bound episode.

[8] Figure A.3 in Appendix C shows the effects of a market variance shock in our VAR for comparison.

[9] 2018 was a rough year for the stock market, characterized by extreme volatility. All major U.S. stock indexes fell substantially, with the S&P 500 and Dow Jones Industrial Average recording their worst daily drops since 1931. The Federal Reserve attributes market developments in 2018 to various factors: "including FOMC communications, weaker-than-expected data, trade policy uncertainties, the partial federal government shutdown, and concerns about the outlook for corporate earnings" (Minutes of the Federal Open Market Committee, January 29-30, 2019, page 14).

the historical narrative provides a useful starting point, it cannot shed light on the underlying mechanism. We thus conduct a more formal investigation into the factors that might be reflected in AC shocks.

To discriminate between different alternatives, we opt for an agnostic approach that lets the data indicate whether there is a single structural shock that resembles orthogonal changes in stock return correlation. We compare the AC shock series to estimates of various structural shocks taken from the existing literature. The following types of shocks are considered: *technology shocks*, including TFP shocks (Justiniano et al., 2011; Francis et al., 2014; Ben Zeev and Khan, 2015; Miyamoto and Nguyen, 2020), investment-specific technology (IST) shocks (Justiniano et al., 2011; Ben Zeev and Khan, 2015; Miyamoto and Nguyen, 2020), and marginal efficiency of investment (MEI) shocks (Justiniano et al., 2011); *technology news shocks*, including TFP news shocks (Beaudry and Portier, 2006; Barsky and Sims, 2011; Miyamoto and Nguyen, 2020) and IST news shocks (Ben Zeev and Khan, 2015; Miyamoto and Nguyen, 2020); *financial shocks* that capture exogenous variation in credit supply conditions (Gilchrist and Zakrajsek, 2012); *fiscal policy shocks*, including anticipated and unanticipated tax shocks (Romer and Romer, 2010; Mertens and Ravn, 2011, 2014) and military spending news shocks (Ben Zeev and Pappa, 2017; Ramey and Zubairy, 2018); *monetary policy shocks*, including those identified from narrative information (Romer and Romer, 2004; Wieland and Yang, 2020) and high-frequency financial market data (Barakchian and Crowe, 2013; Gertler and Karadi, 2015), and shocks that are orthogonal to central bank information surprises (Jarocinski and Karadi, 2020; Miranda-Agrippino and Ricco, 2021); and *trade policy shocks* that capture the announcement effects of future trade restrictions (Metiu, 2021).

Table 3 provides an overview of the various structural shock series.[10] The table also reports the contemporaneous sample correlation between the AC shock series and each of the structural shocks. AC shocks are largely independent from exogenous changes in

[10]Time series of TFP shocks, TFP news shocks, IST shocks, IST news shocks, MEI shocks, defense spending news shocks, and tax shocks were retrieved from Ramey (2016). The remaining shock series were obtained from the original sources indicated in Table 3. Following Ramey (2016), shock series that are serially correlated were filtered with a univariate AR(2) model.

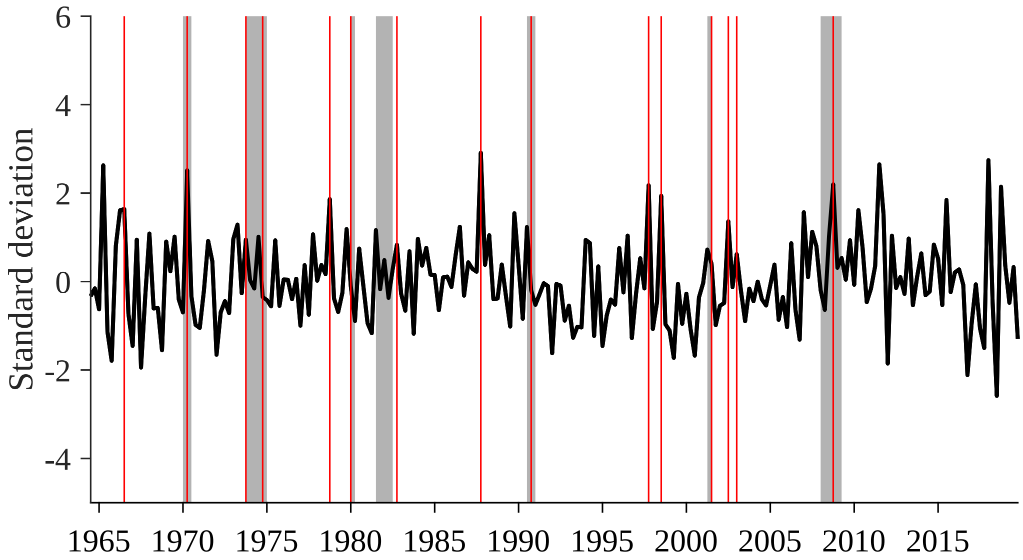


Figure 4: **Estimated AC shock series**

Notes: This figure depicts the AC shock sequence estimated from the benchmark VAR using a recursive scheme with AC_t ordered first. The shaded regions represent recession periods dated by the NBER. The vertical red lines denote 16 historical events dated by Bloom (2009). Sample: 1964Q3-2019Q4.

technology, as well as fiscal, monetary, and trade policy. TFP news shocks and financial shocks arise instead as potential candidates for what gives rise to AC innovations. Beaudry and Portier (2006) extract two shocks from a recursive system that comprises TFP and stock prices: a surprise technology shock that instantaneously moves both TFP and stock prices, and a TFP news shock identified as the innovation to stock prices that is orthogonal to current TFP. We find a highly statistically significant positive correlation between the AC shock series and their TFP news shock (Corr.=0.47).[11] Instead of relying on information contained in stock prices, Barsky and Sims (2011) identify a news shock as the innovation orthogonal to current TFP that best explains variation in future TFP over a ten-year horizon. The AC shock is positively correlated with the Barsky and Sims (2011) TFP news shock series, albeit less strongly than with the Beaudry and Portier (2006) shock series (Corr.=0.19). Finally, the AC shock is positively correlated with the AR(2)-filtered excess bond premium (EBP) proposed by Gilchrist and Zakrajsek (2012) (Corr.=0.29). The EBP is the component of U.S. corporate bond spreads that is not

[11] We extend the Beaudry and Portier (2006) shock series between 2015Q3 and 2019Q4 using their bivariate VAR specification and short-run restrictions with utilization-adjusted TFP and the S&P 500 index in log-levels.

attributable to individual firms' default risk. It can thus be thought of as a measure for financial shocks that capture changes in general investor sentiment in the credit market.

Figure 5 illustrates the correspondence between the AC shock series and the three shock series with which it positively correlates at the 1% significance level. The AC shock and the Beaudry and Portier (2006) TFP news shock move closely together throughout almost the entire sample period, with the exception of brief episodes in the 1980s and the 2010s. There are also similarities between the AC shock and the Barsky and Sims (2011) TFP news shock mainly in the 1970s and the 1990s. At the same time, AC shocks have started to resemble financial shocks from 2000 onward. The uncovered correlation patterns of course do not allow drawing conclusions with regard to causality. Yet, the close association with TFP news shocks and financial shocks is remarkable.[12]

We compare the impulse responses of macroeconomic variables implied by the AC shock with the Beaudry and Portier (2006) TFP news shock and the Gilchrist and Zakrajsek (2012) financial shock, depicted in Figure 6.[13] These are estimated from a VAR specification augmented with the utilization-adjusted TFP series proposed by Fernald (2014), which is a key variable in the news shock literature. We apply the same recursive identification scheme with each of the shock series successively entering the VAR in the first place. The effects of a financial shock are in line with the effects of an AC shock, with one important exception. The financial shock leads to a strong and persistent *decrease* in prices, as already documented by Gilchrist and Zakrajsek (2012). This discrepancy is key, as it allows us to rule out the financial shock interpretation. By contrast, the macroeconomic effects of an AC shock are essentially identical to those of a TFP news shock, with 68% confidence bands overlapping for almost all variables and horizons. Most importantly, the AC shock shares the crucial feature of a TFP new shock that prices and

[12]For comparison purposes, we simulate one million random normal shock sequences for $T = 222$ periods with mean and variance equal to those of the Beaudry and Portier (2006) shock series. The correlation coefficient between the AC shock series and the simulated shocks ranges between -0.32 and 0.36, while 99% of the correlation coefficients fall into the interval [-0.17, 0.17].

[13]The effects of a TFP news shock identified using the Barsky and Sims (2011) shock series are broadly in line with the effects obtained using the Beaudry and Portier (2006) series. Both shocks operate via the supply side as shown in Figure A.4 in Appendix C.

Source	Type of shock	AR(2)	Corr.	Sample
Justiniano et al. (2011)	TFP shock	No	0.01	1964Q1-2009Q1
Francis et al. (2014)	TFP shock	No	0.08	1964Q1-2009Q4
Ben Zeev and Khan (2015)	TFP shock	No	-0.03	1964Q1-2012Q1
Miyamoto and Nguyen (2020)	TFP shock (perm.)	No	0.10	1964Q1-2006Q4
Miyamoto and Nguyen (2020)	TFP shock (stat.)	No	0.08	1964Q1-2006Q4
Justiniano et al. (2011)	IST shock	No	0.08	1964Q1-2009Q1
Ben Zeev and Khan (2015)	IST shock	No	0.09	1964Q1-2012Q1
Miyamoto and Nguyen (2020)	IST shock (perm.)	Yes	0.09	1964Q1-2006Q4
Miyamoto and Nguyen (2020)	IST shock (stat.)	Yes	0.05	1964Q1-2006Q4
Justiniano et al. (2011)	MEI shock	Yes	0.03	1964Q1-2009Q1
Beaudry and Portier (2006)	TFP news shock	No	0.47***	1964Q1-2019Q4
Barsky and Sims (2011)	TFP news shock	No	0.19***	1964Q1-2007Q3
Miyamoto and Nguyen (2020)	TFP news shock (perm.)	Yes	-0.02	1964Q1-2006Q4
Miyamoto and Nguyen (2020)	TFP news shock (stat.)	No	0.12	1964Q1-2006Q4
Ben Zeev and Khan (2015)	IST news shock	No	0.04	1964Q1-2012Q1
Miyamoto and Nguyen (2020)	IST news shock (perm.)	Yes	0.11	1964Q1-2006Q4
Miyamoto and Nguyen (2020)	IST news shock (stat.)	Yes	0.10	1964Q1-2006Q4
Gilchrist and Zakrajsek (2012)	Credit supply shock	Yes	0.29***	1973Q1-2019Q4
Romer and Romer (2010)	Tax shock	No	0.04	1964Q1-2007Q4
Mertens and Ravn (2011)	Tax shock (unanticipated)	No	0.13	1964Q1-2007Q4
Mertens and Ravn (2011)	Tax shock (anticipated)	No	0.04	1964Q1-2007Q4
Mertens and Ravn (2014)	Tax shock (unanticipated)	No	0.11	1964Q1-2007Q4
Ben Zeev and Pappa (2017)	Defense news shock	No	-0.02	1964Q1-2007Q4
Ramey and Zubairy (2018)	Defense news shock	No	-0.10	1964Q1-2013Q4
Romer and Romer (2004)	Monetary policy shock	No	0.06	1969Q1-1996Q4
Wieland and Yang (2020)	Monetary policy shock	No	0.04	1969Q1-2007Q4
Barakchian and Crowe (2013)	Monetary policy shock	No	-0.09	1988Q4-2008Q2
Gertler and Karadi (2015)	Monetary policy shock	No	0.01	1990Q4-2012Q2
Jarocinski and Karadi (2020)	Monetary policy shock	No	0.02	1990Q1-2016Q4
Miranda-Agrippino and Ricco (2021)	Monetary policy shock	No	-0.03	1991Q1-2009Q4
Metiu (2021)	Trade policy shock	No	0.08	1988Q2-2015Q4

Table 3: Correlation between AC shock series and selected structural shocks

Notes: This table reports the correlation coefficients (Corr.) between the estimated AC shock series and selected structural shock series. *** and * denote significance at the 1% and 10% level, respectively. The first column indicates the original sources of the shock series. The third column shows whether the shock series were filtered with a univariate AR(2) model to remove serial correlation. Shock series are available for the sample period indicated in the last column.

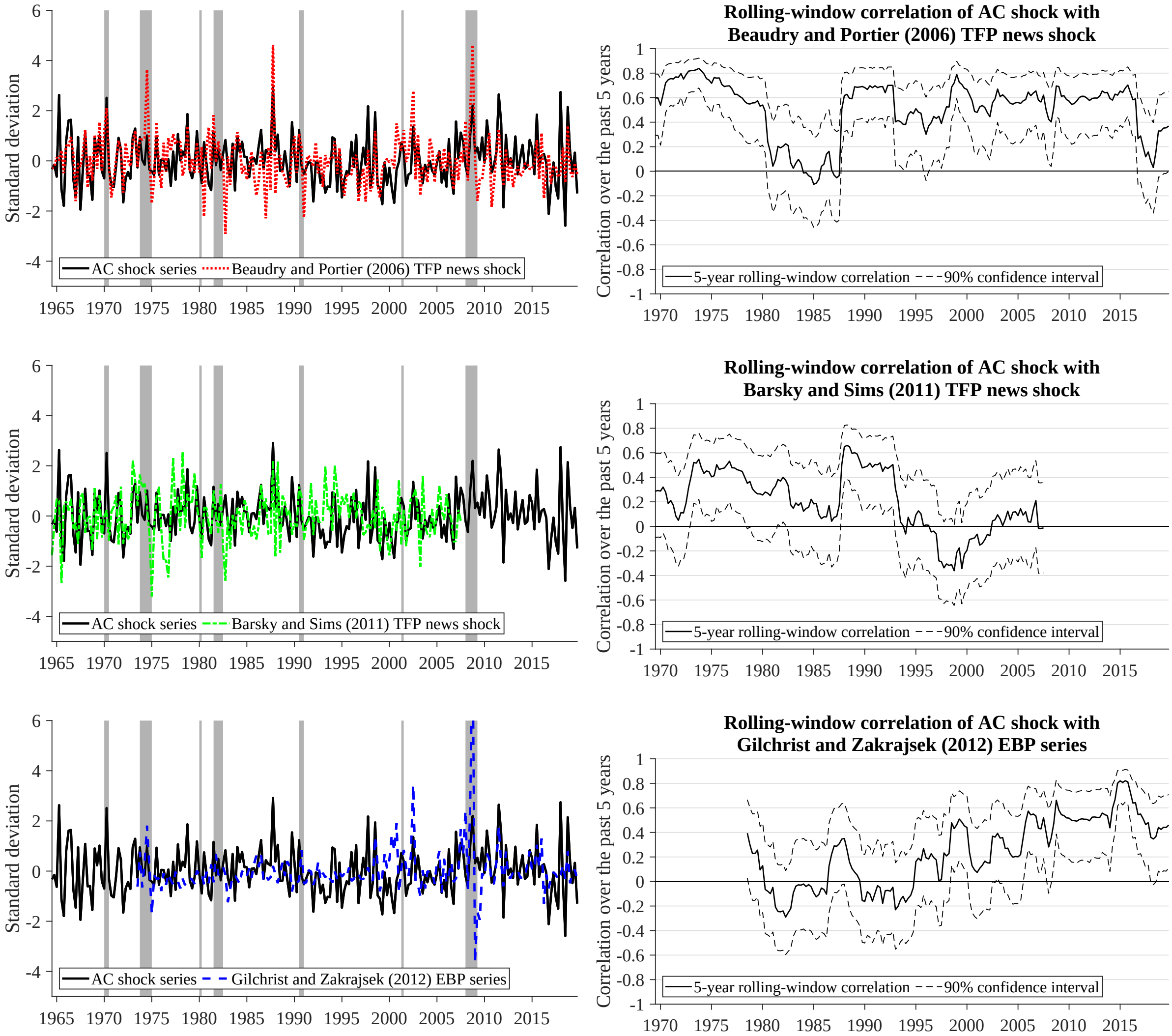


Figure 5: **Estimated AC shock together with selected shock series**

Notes: Left panel: AC shock sequence estimated from the VAR (black solid line) together with selected structural shock series: Beaudry and Portier (2006) TFP news shock for the period 1964Q1-2019Q4 (red dotted line); Barsky and Sims (2011) TFP news shock for the period 1964Q1-2007Q3 (green dashed-dotted line); and Gilchrist and Zakrajsek (2012) AR(2)-filtered EBP shock for the period 1973Q1-2019Q4 (blue dashed line). Right panel: Five-year rolling-window correlation between the AC shock and each structural shock (solid lines) with 90% confidence interval (dashed lines).

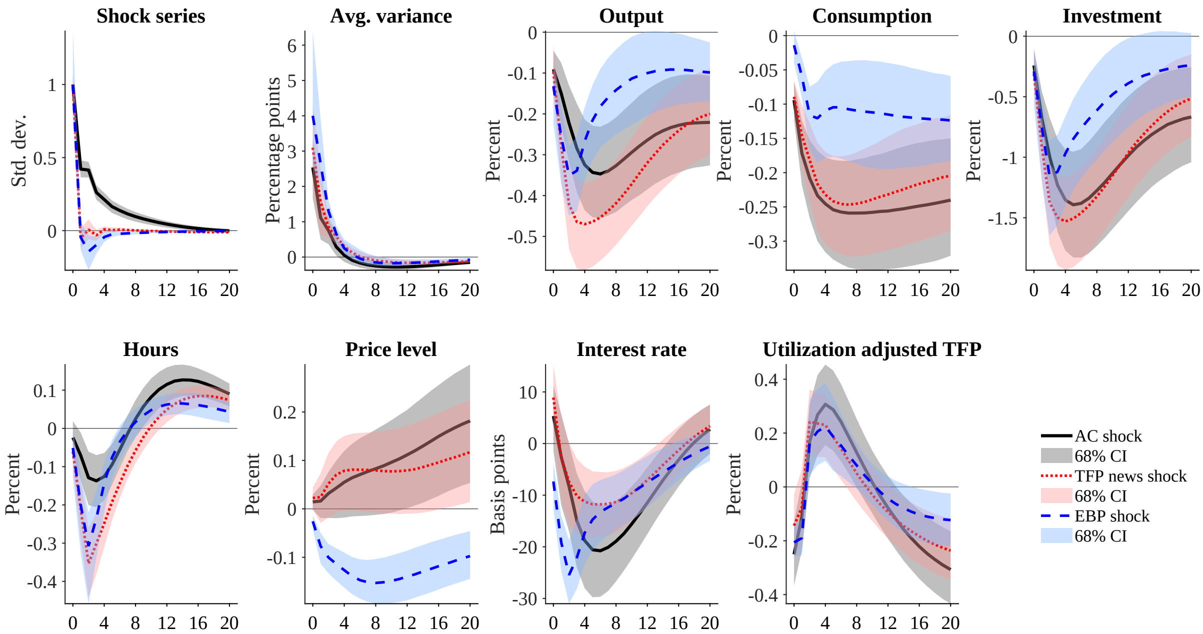


Figure 6: **Impulse responses implied by three different shocks**

Notes: The figure depicts impulse responses to an orthogonal one-standard-deviation increase in AC (black solid lines); the Beaudry and Portier (2006) TFP news shock series (red dotted lines); and the Gilchrist and Zakrajsek (2012) EBP shock series (blue dashed lines), together with 68% bootstrap confidence intervals (shaded areas). The x-axis shows quarters after the shock.

output move in opposite directions.

4 Conclusion

The volatility of the U.S. stock market spiked during major economic and political events like the Cuban missile crisis, the Black Monday crash, the 9/11 terrorist attacks, and the bankruptcy of Lehman Brothers. In a simple portfolio-theoretic framework, stock market variance can be decomposed into two components: the cross-sectional average variance of individual stock returns and the cross-sectional average correlation of stock returns. In this paper, we investigate the business cycle implications of changes in average variance and average correlation.

Using predictive regressions, we first show that the predictive ability of average correlation is on a par with the slope of the yield curve and significantly exceeds that of some other widely used financial predictors such as average variance or the Gilchrist and Zakrajsek (2012) credit spread. We then study how shocks to average variance and average correlation affect macroeconomic variables in a vector autoregression. An unexpected increase in average variance produces a rapid drop and recovery in output, consumption, investment, and hours, and a persistent decrease in the price level. These dynamics are consistent with an uncertainty shock that temporarily reduces aggregate demand. An unanticipated increase in average correlation leads to a significant drop in output, consumption, investment, and hours, as well as to a persistent increase in the price level. These effects last for several years and resemble a negative aggregate supply shock with macroeconomic consequences that emerge above and beyond the uncertainty channel.

We find that shocks to average correlation strongly co-vary with news shocks about future productivity. This result helps to explain the supply-side effects. It also suggests that changes in average correlation are useful for forecasting economic growth because they foreshadow changes in future productivity. Finally, to the extent that changes in average correlation reveal changes in aggregate risk, our VAR estimates suggest that TFP news shocks are the key source of aggregate risk priced by the stock market.

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Appendix

A Approximating stock market variance with average variance and average correlation

This appendix derives an approximation for stock market variance with average variance and average correlation following Pollet and Wilson (2010). To obtain the approximation in Equation (2), we rewrite the expression for $\sigma^2_{m,t}$ using basic algebra:

$$\begin{aligned}
\sigma^2_{m,t} &= \sum_{i=1}^{N} w^2_{i,t}\sigma^2_{i,t} + \sum_{i=1}^{N}\sum_{j\neq i} w_{i,t}w_{j,t}\sigma_{i,t}\sigma_{j,t}\rho_{i,j,t} \qquad (12)\\
&= w^2_{1,t}\sigma^2_{1,t} + \ldots w^2_{N,t}\sigma^2_{N,t} + w_{1,t}w_{2,t}\sigma_{1,t}\sigma_{2,t}\rho_{1,2,t} + \cdots + w_{N,t}w_{N-1,t}\sigma_{N,t}\sigma_{N-1,t}\rho_{N,N-1,t}\\
&= w_{1,t}w_{1,t}\sigma_{1,t}\sigma_{1,t}\rho_{1,1,t} + \cdots + w_{N,t}w_{N,t}\sigma_{N,t}\sigma_{N,t}\rho_{N,N,t}\\
&\quad + w_{1,t}w_{2,t}\sigma_{1,t}\sigma_{2,t}\rho_{1,2,t} + \cdots + w_{N,t}w_{N-1,t}\sigma_{N,t}\sigma_{N-1,t}\rho_{N,N-1,t}\\
&= \sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t}w_{j,t}\rho_{i,j,t}\sigma_{i,t}\sigma_{j,t}.
\end{aligned}$$

We now substitute the pairwise stock-specific deviations from average variance, $\xi_{i,j,t} \equiv \sigma_{i,t}\sigma_{j,t}$ - $\bar{\sigma}^2_t$, into this latter expression:

$$\begin{aligned}
\sigma^2_{m,t} &= \sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t}w_{j,t}\rho_{i,j,t}(\bar{\sigma}^2_t + \xi_{i,j,t}) \qquad (13)\\
&= \bar{\sigma}^2_t \sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t}w_{j,t}\rho_{i,j,t} + \sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t}w_{j,t}\rho_{i,j,t}\xi_{i,j,t}\\
&= \bar{\sigma}^2_t\bar{\rho}_t + \sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t}w_{j,t}\rho_{i,j,t}\xi_{i,j,t}.
\end{aligned}$$

Stock market variance $\sigma^2_{m,t}$ is thus equal to the sum of two terms. The first term is the product of average variance and average correlation. The second term is a function of the cross-sectional relationships between weights, pairwise correlations, and the crossproducts of standard deviations. This term is equal to zero in the case of symmetric stocks that have the same individual variance (i.e., $\xi_{i,j,t} = 0$). In that case, Equation (13) simplifies to $\sigma^2_{m,t} = \bar{\sigma}^2_t \bar{\rho}_t$. More generally, as long as stock-specific deviations from average variance are small, Equation (2) constitutes a useful approximation.

B Replicating the results of Pollet and Wilson (2010)

In this section, we replicate the OLS regressions of Pollet and Wilson (2010) on our sample. In particular, we regress contemporaneous and one-quarter-ahead stock market variance on combinations of AV_t and AC_t, and we estimate predictive regressions of the one-quarter-ahead excess return for the stock market on AV_t, AC_t, and some additional financial predictors.

Table A.1 shows the OLS estimation results from the market variance regressions. We corroborate the findings of Pollet and Wilson (2010) that AV_t and AC_t provide a good approximation of contemporaneous stock market variance (Table A.1, top panel). The product of AV_t and AC_t captures the bulk of the variation in MV_t, as evidenced by an R^2 of 0.997 (column (1)). AC_t accounts individually for 23% of the variation in MV_t, while AV_t on its own explains 95% of the variation (columns (2) and (3)). The relationship between market variance and its components is robust to using a linear approximation of Equation (2), adding the COVID-19 pandemic, and using alternative measures of market variance (columns (4) to (7)). In line with Pollet and Wilson (2010), we also find that AV_t and AC_t jointly explain a non-negligible part of up to 27% in one-quarter-ahead market variance, depending on the market variance measure used (see Table A.1, bottom panel). Individually, AV_t proves to be the superior predictor for subsequent market variance (column (3)).

In Table A.2, we replicate the forecasting regressions for the quarterly excess stock market return of Pollet and Wilson (2010) for the period 1964Q1-2019Q4, using AC_t, AV_t and a number of additional predictors in line with Pollet and Wilson (2010). We

	Dependent variable: variance of stock market returns estimated at t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.143	-5.990	-1.092	-3.218	-0.121	-0.001	2.189
	[-4.472]	[-2.530]	[-8.222]	[-3.920]	[-4.839]	[-0.005]	[8.016]
AC_t		16.646		4.486			
		[3.313]		[2.722]			
AV_t			0.724	0.687			
			[23.386]	[18.037]			
$AV_t \times AC_t$	0.933				0.924	0.930	0.667
	[77.401]				[97.746]	[13.251]	[8.148]
R^2	0.997	0.233	0.945	0.960	0.997	0.926	0.747
T	232	232	232	232	224	232	232
	Dependent variable: variance of stock market returns estimated at $t+1$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	1.483	-0.836	1.004	0.404	1.307	1.802	2.993
	[5.271]	[-0.606]	[3.198]	[0.436]	[5.231]	[5.192]	[9.288]
AC_t		6.678		1.264			
		[2.143]		[0.779]			
AV_t			0.316	0.305			
			[5.004]	[4.975]			
$AV_t \times AC_t$	0.384				0.407	0.321	0.398
	[5.536]				[5.071]	[4.685]	[8.005]
R^2	0.170	0.039	0.181	0.182	0.195	0.112	0.269
T	232	232	232	232	224	232	232

Table A.1: Decomposing and predicting stock market variance

Notes: Top panel: OLS estimates from contemporaneous regressions of stock market variance in period t on combinations of AV_t and AC_t. Bottom panel: OLS estimates from predictive regressions of stock market variance in period $t+1$ on combinations of AV_t and AC_t. The dependent variable in columns (1)-(5) is market variance calculated from realized variances and covariances of returns on 49 Fama-French industry portfolios using Equation (7). The dependent variable in column (6) is market variance calculated as the sum of squared daily returns on the S&P 500 index over each quarter. The dependent variable in column (7) is market variance calculated as the spliced values of realized variance (sum of squared daily S&P 500 returns) for the period 1964Q1-1985Q4 and the squared VXO implied volatility index of the Chicago Board Options Exchange from 1986Q1 onward (see Bloom, 2009). AC_t is the cross-sectional average of the pairwise correlation of returns on 49 Fama-French industry portfolios. AV_t is the cross-sectional average of the realized variance of returns on 49 Fama-French industry portfolios. Newey and West (1987) t-statistics with six lags are reported in square-brackets. Columns (1)-(4), (6), and (7) report estimates for the period 1964Q1-2021Q4. Column (5) shows estimates for the period 1964Q1-2019Q4.

corroborate their results that AC is a strong and statistically significant forecaster of excess stock market returns (column (1)). We also confirm their findings that AV has no predictive power for subsequent excess returns, in spite of the relative strength of AV, as compared to AC, as a predictor for stock market variance in Table A.1 (column (2)). When jointly included, AC emerges clearly as the only useful predictor of future excess returns, with robust t-statistic equal to 2.75, indicating significance at the 1% level (column (3)). AC remains statistically significant at the 5% level with a t-statistic equal to 2.30 when we additionally control for market variance MV_t, the Lettau and Ludvigson (2001) consumption-wealth-income ratio cay_t, the price-dividend ratio pd_t, the risk-free rate rf_t, and the lagged dependent variable (column (4)). As in Pollet and Wilson (2010), only cay_t and rf_t are statistically significant regressors in addition to average correlation.

C Additional figures and tables

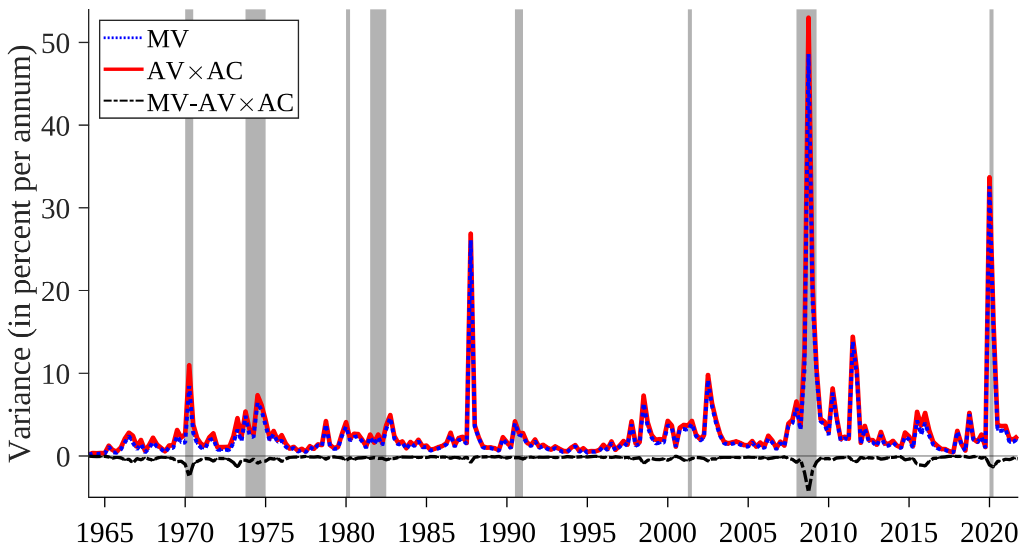


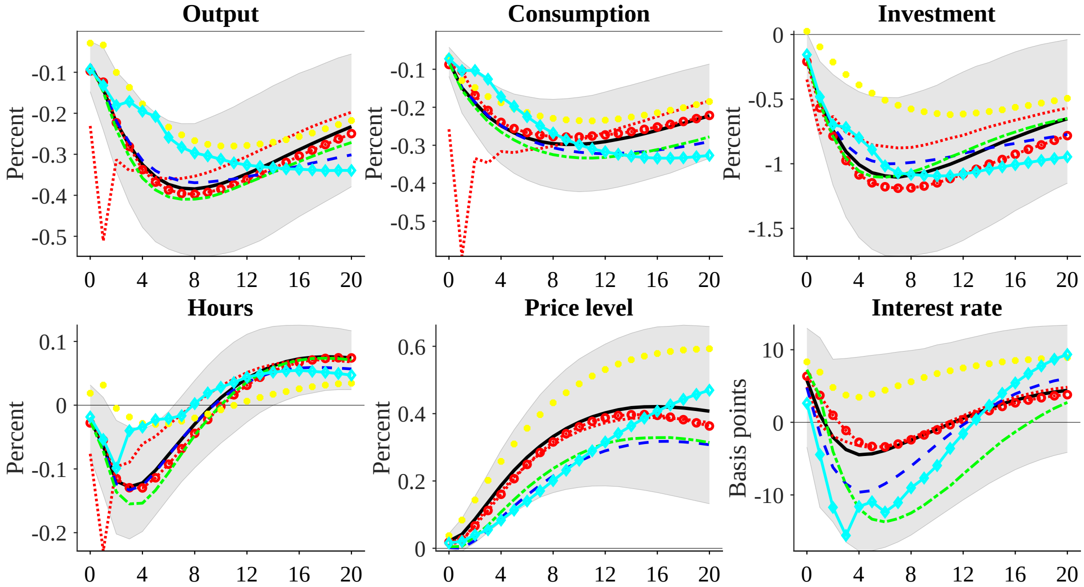
Figure A.1: **Two-component approximation of stock market variance**

Notes: The figure depicts stock market variance MV_t (blue dotted line), its two-component approximation according to the product of AV_t and AC_t in Eq. (2) (red solid line), and the approximation error (black dashed line). The shaded regions represent NBER recession dates. Sample: 1964Q1-2021Q4.

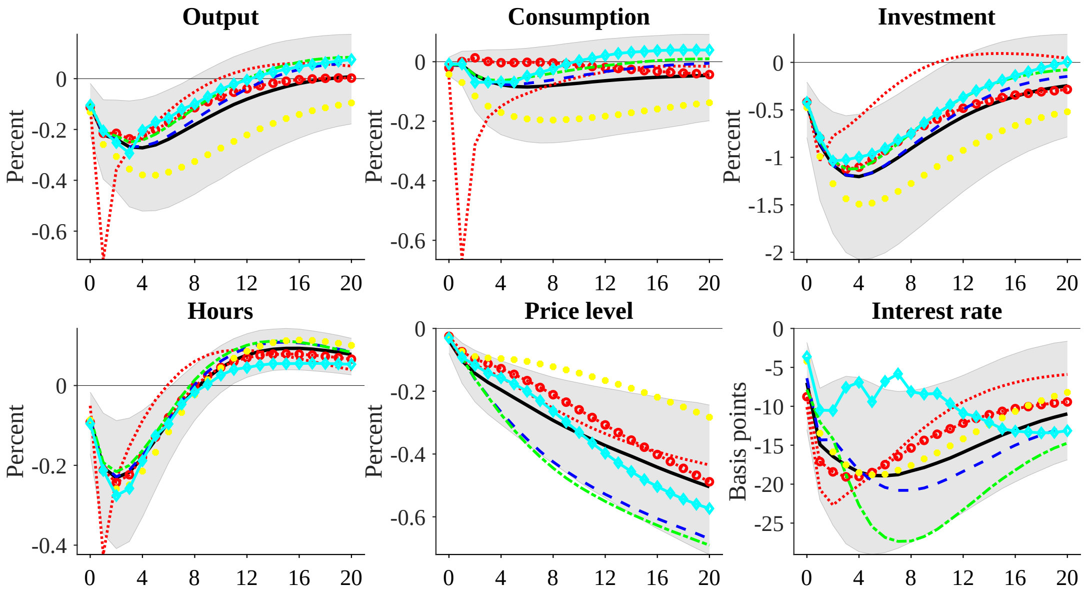
	Dependent variable: excess return for the stock market at $t+1$ (er_{t+1})			
	(1)	(2)	(3)	(4)
Constant	-0.03	0.01	-0.04	0.05
	[1.61]	[0.97]	[1.95]	[0.52]
AC_t	0.07		0.08	0.10
	[1.97]		[2.75]	[2.30]
AV_t		-0.02	-0.13	-0.03
		[0.17]	[1.06]	[0.05]
MV_t				-0.00
				[0.36]
cay_t				0.67
				[2.19]
pd_t				-0.02
				[0.85]
rf_t				-0.53
				[1.92]
er_t				-0.08
				[1.18]
R^2	0.023	0.000	0.031	0.082

Table A.2: Predicting stock market excess returns

Notes: OLS estimates from predictive regressions of the excess return for the stock market at $t+1$ on dependent variables in period t. The dependent variable is the log return on the S&P 500 index minus the 3-month Treasury bill rate in period $t+1$ (er_{t+1}). The independent variables are as follows: AC_t is the cross-sectional average of the pairwise correlation of returns on 49 Fama-French industry portfolios; AV_t is the cross-sectional average of the realized variance of returns on 49 Fama-French industry portfolios; MV_t is market variance calculated from realized variances and covariances of returns on 49 Fama-French industry portfolios using Equation (7); cay_t is the consumption, wealth, income ratio from Lettau and Ludvigson (2001); pd_t is the price-dividend-ratio calculated as the difference between the log of prices and the log of dividends; rf_t is the 3-month Treasury bill rate; and er_t is the dependent variable in period t. Data for er_t, cay_t, pd_t, and rf_t come from the updated data set of Welch and Goyal (2007). Newey and West (1987) t-statistics with five lags are reported in square-brackets. Estimates for the period 1964Q1-2019Q4 are shown.



(a) **Responses to an orthogonal increase in AC**



(b) **Responses to an orthogonal increase in AV**

Figure A.2: **Effects of an orthogonal increase in AC and AV: Robustness**

Notes: Impulse responses to a one-standard-deviation positive shock to AC (top panel) and AV (bottom panel), estimated using the following VAR model specifications: baseline (black solid lines) with 90% bootstrap confidence intervals (gray-shaded areas); sample period extended until 2021Q4 (red dotted lines); sample period extended until 2021Q4 without the observations in 2020Q1-Q2 (red dotted lines with circles); reversed recursive ordering with AV first and AC second, followed by all other variables (yellow stars); *price level* measured by the GDP-deflator (blue dashed lines); *interest rate* measured by the federal funds rate and the Wu and Xia (2016) shadow rate between 2009Q1-2015Q4 (green dashed-dotted lines); and the VAR estimated with four lags (turquoise lines with diamonds). The x-axis shows quarters after the shock.

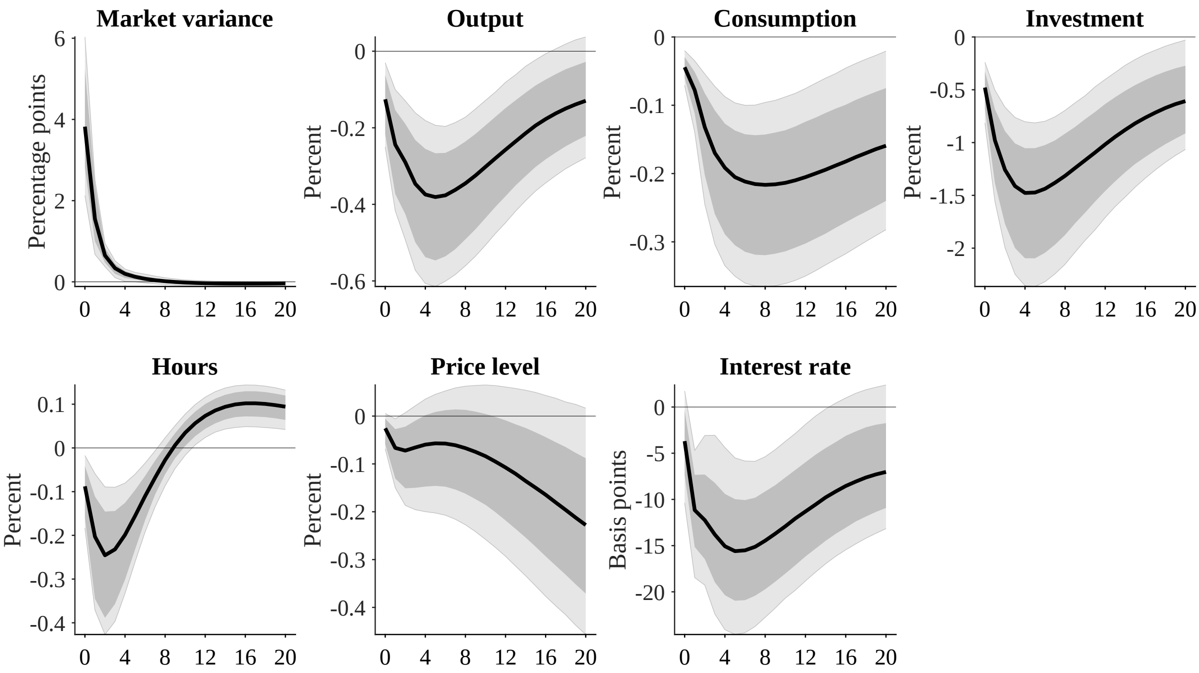


Figure A.3: **Effects of an orthogonal increase in stock market variance**

Notes: The figure depicts impulse responses to a one-standard-deviation positive shock to stock market variance. The shaded areas represent 68% (dark gray) and 90% (light gray) confidence intervals based on 5000 moving block bootstrap replications using the method of Hall (1992). The x-axis shows quarters after the shock.

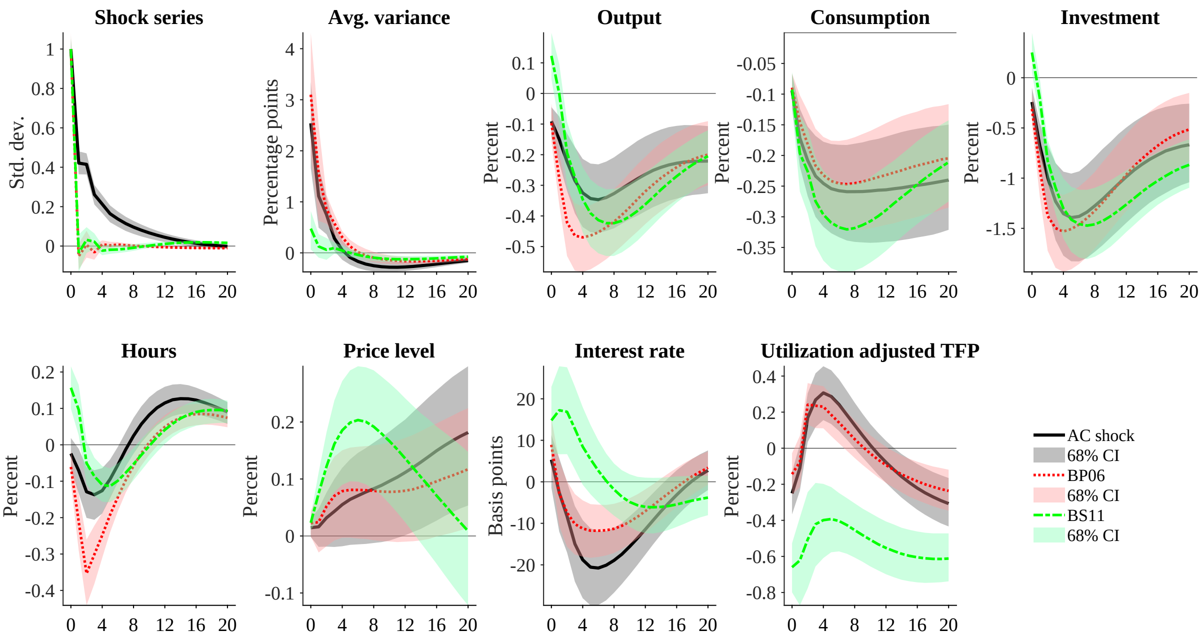


Figure A.4: **Impulse responses to AC shocks and TFP news shocks**

Notes: The figure depicts impulse responses to an orthogonal one-standard-deviation increase in AC (black solid lines); the Beaudry and Portier (2006) TFP news shock series (red dotted lines); and the Barsky and Sims (2011) TFP news shock series (green dashed-dotted lines), together with 68% bootstrap confidence intervals (shaded areas). The x-axis shows quarters after the shock.

	Dependent variable: $\Delta_h GDP_{t+h}$									
	(a) h=4 quarters					(b) h=8 quarters				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
TS_t	-0.41	-0.41	-0.43	-0.42	-0.40	-0.63	-0.62	-0.65	-0.64	-0.62
	[3.67]	[3.67]	[3.82]	[3.71]	[3.51]	[4.34]	[4.46]	[4.62]	[4.36]	[4.21]
RFF_t	0.17	0.01	0.15	0.15	-0.03	0.36	0.23	0.34	0.34	0.20
	[1.27]	[0.04]	[1.12]	[1.16]	[0.22]	[2.24]	[1.38]	[2.16]	[2.13]	[1.09]
GZ_t		-0.43			-0.52		-0.31			-0.38
		[3.63]			[3.31]		[2.14]			[1.81]
MV_t			-0.23		0.18			-0.20		0.15
			[4.61]		[2.05]			[3.94]		[1.40]
AC_t				-0.19	-0.21				-0.23	-0.26
				[2.20]	[2.24]				[2.14]	[2.17
Adj. R^2	0.18	0.31	0.22	0.21	0.33	0.31	0.38	0.34	0.36	0.41
TS_t	-0.69	-0.68	-0.71	-0.69	-0.67	-0.70	-0.68	-0.71	-0.69	-0.66
	[4.07]	[4.25]	[4.37]	[4.10]	[3.92]	[3.67]	[3.78]	[3.89]	[3.67]	[3.41]
RFF_t	0.53	0.43	0.50	0.50	0.41	0.68	0.59	0.67	0.66	0.53
	[2.83]	[2.00]	[2.71]	[2.64]	[1.71]	[3.32]	[2.42]	[3.24]	[3.20]	[2.01]
GZ_t		-0.23			-0.27		-0.27			-0.33
		[1.19]			[0.96]		[1.23]			[1.01]
MV_t			-0.20		0.08			-0.23		0.13
			[3.38]		[0.57]			[3.96]		[0.79]
AC_t				-0.28	-0.30				-0.33	-0.36
				[2.35]	[2.40]				[2.61]	[2.62]
Adj. R^2	0.36	0.39	0.40	0.43	0.46	0.41	0.45	0.45	0.50	0.54

Table A.3: Financial predictors of economic activity, 1973Q1-2019Q4 (with MV)

Notes: This table reports results from a predictive regression of U.S. real GDP growth h quarters into the future, $\Delta_h GDP_{t+h}$, on financial predictors. Panels (a) to (d) contain the results for forecast horizons of $h \in \{4, 8, 12, 16\}$ quarters. Column (1) reports estimates from a specification that includes the term spread, TS_t, and the real federal funds rate, RFF_t. Columns (2) to (4) report estimates that additionally include the Gilchrist and Zakrajsek (2012) credit spread, GZ_t, the market variance based on 49 Fama-French industry portfolios, MV_t, and the (Fisher Z-transformed) cross-sectional average correlation of returns on 49 Fama-French industry portfolios, AC_t, one at a time. Column (5) reports estimates from a specification that simultaneously includes all five financial variables. Each specification also includes a constant and p lags of GDP growth (not reported), where p is determined by the AIC. Entries in the table denote the standardized estimates of the OLS coefficients. Absolute asymptotic t-statistics computed based on Hodrick (1992) 1B standard errors are reported in square-brackets. In-sample goodness of fit is measured by the adjusted R^2.

	Dependent variable: $\Delta_h GDP_{t+h}$									
	(a) h=4 quarters					(b) h=8 quarters				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
TS_t	-0.41	-0.43	-0.40	-0.42	-0.45	-0.64	-0.64	-0.65	-0.65	-0.65
	[1.56]	[1.68]	[1.68]	[1.64]	[1.97]	[5.28]	[5.60]	[5.53]	[5.26]	[5.42]
RFF_t	0.19	0.04	0.15	0.17	0.02	0.37	0.28	0.36	0.36	0.25
	[0.80]	[0.18]	[0.73]	[0.74]	[0.06]	[2.61]	[1.89]	[2.54]	[2.53]	[1.56]
GZ_t		-0.44			-0.54		-0.27			-0.33
		[4.31]			[1.72]		[2.03]			[1.57]
AV_t			-0.23		0.18			-0.17		0.12
			[1.57]		[0.53]			[2.91]		[0.95]
AC_t				-0.21	-0.19				-0.20	-0.19
				[2.09]	[1.83]				[1.97]	[1.79]
Adj. R^2	0.12	0.27	0.17	0.16	0.29	0.34	0.39	0.36	0.37	0.41
	(c) h=12 quarters					(d) h=16 quarters				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
TS_t	-0.69	-0.69	-0.70	-0.70	-0.69	-0.68	-0.67	-0.69	-0.69	-0.68
	[4.61]	[5.02]	[4.90]	[4.62]	[4.80]	[4.10]	[4.39]	[4.32]	[4.15]	[4.09]
RFF_t	0.54	0.47	0.53	0.53	0.48	0.68	0.61	0.67	0.68	0.58
	[3.28]	[2.59]	[3.20]	[3.19]	[2.30]	[3.85]	[2.95]	[3.75]	[3.81]	[2.43]
GZ_t		-0.19			-0.19		-0.25			-0.31
		[1.12]			[0.67]		[1.29]			[0.90]
AV_t			-0.17		0.02			-0.18		0.12
			[2.45]		[0.16]			[2.77]		[0.61]
AC_t				-0.21	-0.22				-0.30	-0.31
				[1.88]	[1.86]				[2.52]	[2.46]
Adj. R^2	0.39	0.41	0.41	0.43	0.45	0.43	0.47	0.46	0.51	0.55

Table A.4: Financial predictors of economic activity, 1973Q1-2021Q4 (with COVID-19)

Notes: This table reports results from a predictive regression of U.S. real GDP growth h quarters into the future, $\Delta_h GDP_{t+h}$, on financial predictors. Panels (a) to (d) contain the results for forecast horizons of $h \in \{4, 8, 12, 16\}$ quarters. Column (1) reports estimates from a specification that includes the term spread, TS_t, and the real federal funds rate, RFF_t. Columns (2) to (4) report estimates that additionally include the Gilchrist and Zakrajsek (2012) credit spread, GZ_t, the cross-sectional average variance of returns on 49 Fama-French industry portfolios, AV_t, and the (Fisher Z-transformed) cross-sectional average correlation of returns on 49 Fama-French industry portfolios, AC_t, one at a time. Column (5) reports estimates from a specification that simultaneously includes all five financial variables. Each specification also includes a constant and p lags of GDP growth (not reported), where p is determined by the AIC. Entries in the table denote the standardized estimates of the OLS coefficients. Absolute asymptotic t-statistics computed based on Hodrick (1992) 1B standard errors are reported in square-brackets. In-sample goodness of fit is measured by the adjusted R^2.

D Data

Stock market variance (MV_t). The baseline measure of stock market variance is calculated from the quarterly realized variances and covariances of returns on 49 Fama and French (1997) industry portfolios using equal weights (see Equation (7)). Daily value-weighted returns on NYSE, AMEX, and Nasdaq stocks sorted into 49 industry portfolios were retrieved from the Fama-French Data Library.[14] For the sake of robustness, we calculate two further measures of stock market variance. The second measure is the quarterly realized variance of the S&P 500 index. Data on the S&P 500 composite price index at the daily frequency come from Yahoo Finance (code: *GSPC*). The third measure of stock market variance is obtained as the squared values of realized volatility (from 1964Q1 to 1985Q4) and implied volatility (from 1986Q1 to 2021Q4), following Bloom (2009). Implied volatility is measured by the CBOE S&P 100 Volatility Index (VXO), retrieved from the Federal Reserve Bank of St. Louis (code: *VXOCLS*). Realized volatility is measured by the quarterly realized standard deviation of daily S&P 500 returns normalized to the same mean and variance as the VXO index.

Average variance (AV_t). The equally weighted cross-sectional average of the quarterly realized variance of daily returns on 49 Fama-French industry portfolios (see Equation (8)).

Average correlation (AC_t). The equally weighted cross-sectional average of the pairwise correlations of daily returns during each quarter for all pairs of the 49 Fama-French

[14]Retrieved in February 2022 from: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. The industries are: agriculture; food products; candy and soda; beer and liquor; tobacco products; recreation; entertainment; printing and publishing; consumer goods; apparel; healthcare; medical equipment; pharmaceutical products; chemicals; rubber and plastic products; textiles; construction materials; construction; steel and metal industries; fabricated products; machinery; electrical equipment; automobiles and trucks; aircraft; shipbuilding, railroad equipment; defense; precious metals; non-metallic and industrial metal mining; coal; petroleum and natural gas; utilities; telecommunication; personal services; business services; computers; computer software; electronic equipment; measuring and control equipment; business supplies; shipping containers; transportation; wholesale; retail; restaurants, hotels, motels; banking; insurance; real estate; trading (finance); other (incl. sanitary services; steam, air conditioning supplies; irrigation systems; and cogeneration).

industry portfolios (see Equation (9)).

Consumption. Consumption is the sum of nondurable and services consumption, following Basu and Bundick (2017). Nondurable consumption is measured by real personal consumption expenditures on nondurable goods in billions of chained 2012 U.S. dollars (source: U.S. Bureau of Economic Analysis, retrieved from FRED, Federal Reserve Bank of St. Louis; code: *PCNDGC96*, extended backwards with *DNDGRL1Q225SBEA*). Services consumption is measured by real personal consumption expenditures on services in billions of chained 2012 U.S. dollars (source: U.S. Bureau of Economic Analysis, retrieved from FRED; code: *PCESVC96*, extended backwards with *DSERRL1Q225SBEA*). We convert consumption to per capita terms by dividing by the civilian noninstitutional population, defined as persons 16 years of age and older residing in the 50 states and the District of Columbia, who are not inmates of institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces (source: U.S. Bureau of Labor Statistics, retrieved from FRED; code: *CNP16OV*).

Investment. Investment is the sum of durable consumption and business fixed investment, following Basu and Bundick (2017). Durable consumption is measured as real personal consumption expenditures on durable goods in billions of chained 2012 U.S. dollars (source: U.S. Bureau of Economic Analysis, retrieved from FRED; code: *PCDGCC96*, extended backwards with *DDURRL1Q225SBEA*). Business fixed investment is measured as real private fixed investment in billions of chained 2012 U.S. dollars (source: U.S. Bureau of Economic Analysis, retrieved from FRED; code: *FPIC1*, extended backwards with *A007RL1Q225SBEA*). We convert investment to per capita terms by dividing by the civilian noninstitutional population.

GDP. Real gross domestic product in billions of chained 2012 U.S. Dollars. Quarterly, seasonally adjusted annual rate. Source: U.S. Bureau of Economic Analysis, retrieved from FRED (code: *GDPC1*). We convert GDP to per capita terms by dividing by the civilian noninstitutional population.

GZ spread. Gilchrist and Zakrajsek (2012) corporate credit spread. Source: Favara et al. (2016).[15]

Hours worked. Average weekly hours per worker of production and nonsupervisory employees: manufacturing. Quarterly, seasonally adjusted. Source: U.S. Bureau of Labor Statistics, retrieved from FRED (code: *AWHMAN*).

One-year Treasury yield. Market yield on U.S. Treasury securities at one-year constant maturity. Source: Board of Governors of the Federal Reserve System (U.S.), retrieved from FRED (code: *DGS1*).

Price level. The baseline measure is the chain-type price index of personal consumption expenditures excluding food and energy (2012=100). Source: U.S. Bureau of Economic Analysis, retrieved from FRED (code: *PCEPILFE*). We use the GDP implicit price deflator (index, 2012=100) in a robustness check. Source: U.S. Bureau of Economic Analysis, retrieved from FRED (code: *GDPDEF*).

Real federal funds rate. The real federal funds rate RFF_t is calculated as the difference between the effective federal funds rate in period t and the core PCE inflation rate between period t-1 and t-5 (see also Gilchrist and Zakrajsek, 2012). Source: Board of Governors of the Federal Reserve System (U.S.), retrieved from FRED, Federal Reserve Bank of St. Louis; code: *FEDFUNDS*.

Term spread. The difference between the three-months constant-maturity Treasury bill

[15] https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html. Retrieved in February 2022.

secondary market yield (source: Board of Governors of the Federal Reserve System (U.S.), retrieved from FRED; code: *TB3MS*) and the market yield on U.S. Treasury securities at 10-year constant maturity (source: Board of Governors of the Federal Reserve System (U.S.), retrieved from FRED; code: *DGS10*).

Unemployment rate. Civilian unemployment rate: number of unemployed as a percentage of the labor force. Quarterly, seasonally adjusted. Source: U.S. Bureau of Labor Statistics, retrieved from FRED (code: *UNRATE*).

Utilization-adjusted TFP. Utilization-adjusted TFP for the U.S. business sector produced by John Fernald. Source: Federal Reserve Bank of San Francisco and Fernald (2014) (code: *dtfp-util*).[16]

[16] https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/. Retrieved in February 2022.