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Option Valuation with Macro-Finance Variables

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Abstract

I propose a model in which the price of an option is partly determined by macro-finance variables. In an application using an index of current business conditions, the new model outperforms existing benchmarks in fitting underlying asset returns and in pricing options. The model performs particularly well when business conditions are deteriorating. Using the recent financial crisis as an out-of-sample experiment, the new model has option-pricing errors that are 18% below those of a nested 2-component volatility benchmark. Results are robust to using alternative business conditions proxies and comparing to different benchmark models.

I. Introduction

In an efficient market, public information should be accounted for in the price of a derivative's underlying asset. Assuming constant volatility, public information has no further impact on the price of the derivative. This was at the core of the groundbreaking Black and Scholes (1973) formula. In a valuation model acknowledging the stochastic nature of volatility, however, the price of the derivative also depends on the expected distribution of future volatility. Option values may therefore be functions of additional variables that are not perfectly correlated with stock returns. Latent stochastic volatility models, following Heston's (1993) work, acknowledge this reality but require imperfect filtering of the unobserved volatility process.

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In this article, I propose an option-valuation model, the MacroGARCH model, in which I consider the possibility that, instead of being affected by latent factors, option values are partly determined by observable economic variables. That is, in my framework, for the same underlying price and current variance, the price of an option can differ depending on macro-finance variables. A natural first application for this new framework is to study how business conditions, through their impact on conditional volatility expectations, can affect option prices.

Following the seminal paper of Schwert (1989), a large body of literature has investigated the measurement of stock market volatility through business cycles. In particular, recent studies by Engle and Rangel (2008) and Engle, Ghysels, and Sohn (EGS) (2013) successfully develop generalized autoregressive conditional heteroskedasticity (GARCH) models in which volatility varies around a fundamental volatility level determined by economic fundamentals. EGS find that this fundamental volatility process is significantly related to such factors as inflation and industrial production growth even at short horizons.[1] These results confirm those of Engle and Rangel who provide evidence that high inflation and slow growth of output increase volatility, as does volatility in macroeconomic factors such as gross domestic product (GDP) growth, inflation, and short-term interest rates. Both studies show that accounting for economic fundamentals significantly improves volatility forecasts. I extend their work and analyze the option-valuation properties of volatility models that account for changes in business conditions.

A considerable number of macro-finance variables could be used in my framework. My choice is driven by a simple motivation: using as much information as possible, in a parsimonious and convenient manner. In linear predictive regressions, Paye (2012) finds that whereas macroeconomic variables hardly improve volatility forecasts when taken in isolation, they yield significantly better forecasts when combined. Option-based objective functions, however, tend to favor relatively parsimonious models (Christoffersen and Jacobs (2004)). Consequently, I suggest a parsimonious fundamental volatility process evolving with changes in business conditions, as proxied by a single index combining six widely followed macroeconomic indicators. The Aruoba, Diebold, and Scotti (ADS) (2009) business conditions index, published by the Federal Reserve (Fed) Bank of Philadelphia, is easy to interpret, timely, and conveniently updated on the Fed's Web site as data on the index's underlying components are released.[2]

I first consider a simple version of my MacroGARCH model. By setting a single parameter to zero, the business conditions variable is disregarded and the MacroGARCH model reduces to the nonaffine GARCH (NGARCH) model of Duan (1995), which Hsieh and Ritchken (2005) and Christoffersen, Dorion, Ja-

[1] EGS (2013) refer to the fundamental volatility process as the secular volatility process. They model it in a mixed data sampling (MIDAS) framework (see, e.g., Ghysels, Santa-Clara, and Valkanov (2005), Forsberg and Ghysels (2007), Ghysels, Sinko, and Valkanov (2007), and EGS (2013)). Regime-switching models (Hamilton and Susmel (1994)) provide another framework to model changing business conditions. The unobserved regime model of David and Veronesi (2002) exploits this approach. Conversely, using economic fundamentals has the advantage of identifying the determinants of gradual changes in conditional volatility expectations.

[2] The Web page of the index is www.phil.frb.org/research-and-data/real-time-center/business-conditions-index/.

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cobs, and Wang (CDJW) (2010) find to have better option-valuation properties than its affine counterpart (Heston and Nandi (2000)).[3] Model parameters are estimated by maximum likelihood using Standard & Poor's (S&P) 500 returns and the likelihood ratio test significantly favors the MacroGARCH model over the NGARCH benchmark.

Using the risk-neutralized MacroGARCH model enables a cross-sectional analysis of option-pricing errors on 21 years of weekly options data, one of the most extensive data sets analyzed in the option-valuation literature. During these 21 years, the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) is on average 18.8% in expansions. On an average recession day, the VIX is 11.1% higher. This difference is statistically significant at any reasonable level and is of clear economic significance; an at-the-money-forward, 1-month-to-maturity option is approximately 59% more expensive on an average recession day. During the three recessions spanned by my data set, the MacroGARCH model yields pricing errors that are between 15% and 42% lower than the errors obtained using a model that disregards business conditions. These results hold during the Great Recession, which is treated fully out of sample. Between Dec. 2007 and Oct. 2010, the MacroGARCH model is on average 23% more accurate than its benchmark, with improvements ranging from 10% to 32% depending on moneyness and maturity.

I then proceed to assess the robustness of my results in a multicomponent framework. Indeed, the MacroGARCH model conceptually allows for 2 volatility components: the fundamental volatility and a high-frequency volatility component that varies around the fundamental volatility. The finding that such models better describe stock market volatility and option prices is consistent with the growing consensus that 2-factor volatility processes more effectively capture the time-series properties of volatility by separately accounting for transient and highly persistent volatility shocks.[4] However, comparing the low-frequency volatility of Engle and Lee (1999), for instance, to my fundamental volatility, it appears that they capture different features of volatility.

Consequently, inspired by the work on multifrequency news and volatility by Calvet and Fisher (2001), (2002), (2003), and (2007), I suggest a model with 3 volatility components: a high-frequency volatility component, which evolves around a low-frequency volatility component, which in turn evolves around time-varying volatility expectations described by the fundamental volatility process. This model, referred to as the MacroGARCH(C) model, nests the nonaffine component model of Engle and Lee (1999), referred to as the NGARCH(C), and the simple MacroGARCH model.

Compared to the NGARCH(C), the MacroGARCH(C) model is still 18% more accurate, on average, than its 2-component benchmark out of sample. Moreover, a comparison with an extended model comprising 3 purely autoregressive

[3]In a stochastic volatility framework, Chernov, Gallant, Ghysels, and Tauchen (2003) also find strong empirical support for nonaffine models when estimating on daily S&P 500 returns.

[4]On 2-factor models, see, among others, Engle and Lee (1999), Bates (2000), Andersen, Bollerslev, Diebold, and Ebens (2001), Alizadeh, Brandt, and Diebold (2002), Christoffersen, Jacobs, Ornthanalai, and Wang (2008), Engle and Rangel (2008), CDJW (2010), and Christoffersen, Feunou, Jacobs, and Meddahi (CFJM) (2014).

volatility components clearly illustrates that the fundamental volatility process captures features of volatility expectations that are not captured by autoregressive specifications.

Interestingly, during the 2007–2009 Great Recession, the MacroGARCH model based on the ADS business conditions index significantly outperforms an alternative specification based on the VIX. Whereas option maturities extend over several weeks or months, option-pricing models are typically estimated with daily returns. Consequently, daily volatility dynamics are predominant in the estimation. Although daily volatility dynamics certainly are of first-order importance for option pricing, my results establish that volatility models accounting for economic fundamentals, which evolve at a slower pace, exhibit significantly improved option-valuation properties.

Finally, it is worth noting that both likelihood ratio tests and the comparison of option-pricing errors strongly favor variants of the MacroGARCH model allowing for an asymmetric response of fundamental volatility to good and bad macroeconomic news. In a rational expectations equilibrium setup, Veronesi (1999) shows that stock prices overreact to bad news in good times and underreact to good news in bad times. Veronesi's model further implies that the volatility of returns is asymmetric with respect to macroeconomic news. My results, although based on a reduced-form model, are in line with the implications of Veronesi's model.

The article is organized as follows: Section II presents the MacroGARCH model. Section III discusses an application using business conditions, presents the estimation of the model's parameters using maximum likelihood, and summarizes 21 years of option-pricing errors. Section IV assesses the robustness of my results in a multicomponent framework and using a different macro-finance variable. Section V concludes.

II. The MacroGARCH Model

Dynamic volatility models may be divided into two categories. In a GARCH model, the shocks to the volatility process are a deterministic transformation of the return innovations. By assuming a single source of randomness, GARCH models offer a framework in which, given the observable return process, the filtration of the return shocks is trivial.

In a general stochastic volatility model, the volatility process is driven by unobservable shocks that are only imperfectly correlated with shocks to the return process. Volatility is thus driven partly by return shocks, partly by additional latent variables. As these additional variables move independently of stock returns, they cannot be perfectly filtered using historical stock returns. In this article, I assume that macro-finance variables can be used to proxy for the evolution of these latent variables. With this assumption, I remain in a GARCH-style framework, allowing straightforward estimation of the option-pricing model.

Conceptually, many channels could be used to study the influence of prevailing market conditions on option prices. I focus on how business conditions, through their impact on conditional volatility expectations, affect prices.

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A. Macroeconomic News and Fundamental Volatility

In a typical GARCH model, the return and variance processes are given by:

$$R_{t+1} = \log\left(\frac{S_{t+1}}{S_t}\right) = \mu_{t+1} - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon_{t+1}, \tag{1}$$

$$h_{t+1} = f(\{h_s, \varepsilon_s\}_{s\leq t} \mid \Theta_h), \tag{2}$$

where S_t is the stock price; μ_{t+1}, the conditional expected return, and h_{t+1}, the conditional variance of returns, are $\mathcal{F}_t$ measurable; and Θ_h is a set of variance parameters. I assume that the ε_t innovations are serially uncorrelated, standard normal variables. As highlighted by equation (2), it is common, at least in the GARCH option-pricing literature, to assume that variance depends only on past market shocks and variance levels. I deviate from this assumption by building on recent work by Engle and Rangel (2008) and EGS (2013).

Engle and Rangel (2008) consider a log-linearization of returns that decomposes unexpected returns into a future-cash-flows innovation and an expected-returns innovation (Campbell (1991), Campbell and Shiller (1988)). They show that this decomposition is consistent with a variance specification in which market volatility superimposes over a more fundamental volatility process related to the slowly evolving macroeconomy, that is, a variance process of the form

$$\begin{aligned} h_{t+1} &= f(\{h_s, \varepsilon_s, x_s\}_{s\leq t} \mid \Theta_h) \\ &= f_{\text{mkt}}(\{h_s, \varepsilon_s\}_{s\leq t} \mid \Theta_h) \circ f_{\text{fund}}(\{x_s\}_{s\leq t} \mid \Theta_h), \end{aligned} \tag{3}$$

where transient market shocks to the volatility process are accounted for in a volatility component, f_{mkt}, that captures deviation from a lower frequency component, f_{fund}, describing the evolution of expectations regarding volatility. These expectations are related to observed macro-finance variables, x_t, that change with the fundamentals of the economy. Consequently, in this article, I refer to f_{fund} as the fundamental volatility process.

In particular, Engle and Rangel (2008) consider a model in which

$$h_{t+1} = g_{t+1}\tau_{t+1}, \tag{4}$$

$$g_{t+1} = 1 + \alpha g_t\left(\varepsilon_t^2 - 1\right) + \beta(g_t - 1), \tag{5}$$

$$\tau_{t+1} = f_{\text{fund}}(\{x_s\}_{s\leq t} \mid \Theta_h), \tag{6}$$

where the fundamental volatility, τ_{t+1}, is modeled using a partially nonparametric spline estimator.[5] The unit GARCH process g_t allows market volatility to differ from expectations.

This model nests the simple GARCH(1,1) model (Engle (1982), Bollerslev (1986)). Indeed, under constant fundamental volatility, that is, $\tau_t = \sigma^2, \forall t$,[6]

$$h_{t+1} = g_{t+1}\sigma^2 = \sigma^2 + \alpha h_t\left(\varepsilon_t^2 - 1\right) + \beta(h_t - \sigma^2). \tag{7}$$

[5] Engle and Rangel (2008) express the unit GARCH process as $g_{t+1} = (1-\alpha-\beta') + \alpha g_t\varepsilon_t^2 + \beta' g_t$, which is equivalent to equation (5) with $\beta = \alpha + \beta'$.

[6] The GARCH(1,1) model is most commonly expressed as $h_{t+1} = \omega + \alpha h_t\varepsilon_t^2 + \beta' h_t$, which is equivalent to equation (7) with $\sigma^2 = \omega/(1-\alpha-\beta')$ and $\beta = \alpha + \beta'$. In my formulation, β directly describes volatility persistence.

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This highlights the crucial role played by the τ_t component; it allows volatility expectations to vary through time.

Time-varying expectations can be identified by projecting fundamental volatility on observable macro-finance variables. Engle and Rangel (2008) model fundamental volatility using a spline and relate the extracted process to economic fundamentals via linear regression. For asset-pricing purposes, this approach could become cumbersome because it would involve forecasting the fundamentals and then using the regression coefficients to forecast fundamental volatility out of sample to finally forecast the evolution of out-of-sample high-frequency volatility around the forecasted fundamental volatility.

Conveniently, in subsequent work, EGS (2013) explicitly account for a macroeconomic observable x in the fundamental volatility dynamics of the MIDAS-GARCH model. Building on their methodology, I suggest the following model, which I refer to as the MacroGARCH model:

$$R_{t+1} = r + \lambda\sqrt{h_{t+1}} - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon_{t+1}, \tag{8}$$

$$h_{t+1} = \tau_{t+1} + \alpha h_t\left(\varepsilon_t^2 - 1 - 2\gamma\varepsilon_t\right) + \beta(h_t - \tau_t), \tag{9}$$

$$\tau_{t+1} = \left(1 + \theta\sum_{k=0}^{K-1}\phi_k(w)x_{t-k}\right)\sigma^2, \tag{10}$$

where r is the risk-free rate and x_t is a given macro-finance variable. The ϕ_k weighting scheme, parameterized by w, allows the fundamental volatility process τ_t to load smoothly on recent observations in the mixed data sampling (MIDAS) spirit. That is, x need not be sampled at the same frequency as the returns. In my work, I assume that ϕ_k is a beta weighting scheme,

$$\phi_k(w) = \frac{\left(\frac{1-k}{K}\right)^{w-1}}{\sum_{j=0}^{K-1}\left(\frac{1-j}{K}\right)^{w-1}}, \tag{11}$$

which discards past observations at a rate controlled by w; the larger the w, the faster past observations are discarded.[7]

My MacroGARCH model mildly differs from the model of EGS (2013). The main motivation behind these differences is that I aim to nest, when $\theta = 0$, the NGARCH model of Duan (1995) rather than the GARCH(1,1). The NGARCH model is one of the many models that, by way of the γ parameter, accounts for the asymmetric response of volatility to positive and negative returns, referred to as the leverage effect (Black (1976)). This feature is particularly important when considering the option-valuation properties of a model (see, e.g., Nandi (1998), Heston and Nandi (2000), Chernov and Ghysels (2000), Christoffersen and Jacobs (2004), and Christoffersen, Heston, and Jacobs (2006)). I choose to nest

[7]Beta weights are usually parameterized by two parameters. I omit the parameter allowing for hump-shaped weightings for the sake of parsimony as preliminary experiments showed that it provided little benefit. EGS (2013) do the same in their analysis of daily realized volatility.

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the NGARCH model based on results by Hsieh and Ritchken (2005) and CDJW (2010). Both studies demonstrate that the NGARCH model is superior to its affine counterpart, the AGARCH model of Heston and Nandi (2000), when fitting historical returns and when pricing options.

Finally, note that defining $g_t = h_t/\tau_t$, the additive specification in equations (9) and (10) is observationally equivalent to the multiplicative specification of Engle and Rangel (2008) and EGS (2013). I prefer the additive specification as it is more common in the option-valuation literature. Consequently, it will allow for a straightforward comparison with other component models prevalent in the literature (Section IV.A).

B. Risk Neutralization with Macro-Finance Variables

Candidate variables for x_t in equation (10) abound. Regardless of the chosen variable, I can assume that it evolves dynamically:

$$x_{t+1} = \varphi(\{x_s, u_s\}_{s\le t} \mid \Theta_x) + \sigma_x u_{t+1}, \tag{12}$$

where $u_t \overset{\mathbb{P}}{\sim} \mathcal{N}(0,1)$ are serially uncorrelated innovations.[8] Typically, GARCH option-valuation models include a single source of randomness, the ε_{t+1} innovation of equation (1). However, the u_t shocks to the macro-finance variable introduce a second source of randomness in the MacroGARCH model.

When $\theta = 0$, the innovations to the observable variable are irrelevant, as the MacroGARCH model collapses to Duan's (1995) model

$$R_{t+1} = r + \lambda\sqrt{h_{t+1}} - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon_{t+1}, \tag{13}$$

$$h_{t+1} = \sigma^2 + \alpha h_t\left(\varepsilon_t^2 - 1 - 2\gamma\varepsilon_t\right) + \beta(h_t - \sigma^2). \tag{14}$$

The risk neutralization of Duan (1995) is a special case of Christoffersen, Elkamhi, Feunou, and Jacobs (CEFJ) (2010) in which the equivalent martingale measure (EMM) obtains by assuming that the Radon–Nikodym derivative is linear in stock return innovations.[9] That is,

$$\xi_\tau \equiv \left.\frac{d\mathbb{Q}}{d\mathbb{P}}\right|\mathcal{F}_\tau = \exp\left\{-\sum_{t=1}^{\tau}\left(\eta_t\varepsilon_t + \frac{1}{2}\eta_t^2\right)\right\}. \tag{15}$$

For the $\mathbb{Q}$ measure defined by equation (15) to be an EMM, it must be that

$$1 = \mathbb{E}_{t-1}^{\mathbb{Q}}\left[\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right] = \mathbb{E}_{t-1}^{\mathbb{P}}\left[\frac{\xi_t}{\xi_{t-1}}\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right], \tag{16}$$

[8] The volatility of the series could follow a GARCH process, that is, $\sigma_{x,t+1} = \varphi_\sigma(\{\sigma_{x,s}, u_s\}_{s\le t} \mid \Theta_{\sigma_x})$. For simplicity, I assume constant volatility.

[9] Assuming a linear Radon–Nikodym derivative is very common in the GARCH option-valuation literature. Among many others, it is made either implicitly or explicitly by Duan (1995), Heston and Nandi (2000), Ritchken and Trevor (1999), Stentoft (2005), Christoffersen, Jacobs, and Ornthanalai (2012), and Ornthanalai (2014). As discussed Ornthanalai (2014), it is analog to the affine pricing kernel used, in continuous time, by studies such as Liu, Pan, and Wang (2005), Bates (2006), and Eraker (2008).

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which implies that $\eta_t = \lambda, \forall t$. See Internet Appendix A (available at www.jfqa.org) for details.

Hence, much like in the Black and Scholes (1973) risk neutralization, the distribution of market shocks is translated to the left under the risk-neutral measure $\mathbb{Q}$. The discrete-time analog of the market price of risk

$$\frac{\mu_{t+1} - r}{\sqrt{h_{t+1}}} = \lambda \tag{17}$$

determines the extent of the translation: Under $\mathbb{Q}$, ε_t is distributed $\mathcal{N}(-\lambda, 1)$. This leads to the following risk-neutral form for the NGARCH model:

$$R_{t+1} = r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon^*_{t+1}, \tag{18}$$

where

$$\varepsilon^*_{t+1} = \varepsilon_{t+1} + \lambda \overset{\mathbb{Q}}{\sim} \mathcal{N}(0,1),$$

$$h_{t+1} = \sigma^{*2} + \alpha h_t(\varepsilon^{*2}_t - 1 - 2\gamma^*\varepsilon^*_t) + \beta^*(h_t - \sigma^{*2}), \tag{19}$$

where $\gamma^* = \gamma + \lambda$, $\beta^* = \beta + \alpha(\gamma^{*2} - \gamma^2)$, and $\sigma^{*2} = (1-\beta)\sigma^2/(1-\beta^*)$.

However, when $\theta \neq 0$, the innovations to the observable variable matter and must be risk neutralized. Assuming that the u_ts are serially uncorrelated standard Gaussian, I can decompose the market shocks, ε_t, as follows:

$$\varepsilon_t = \rho u_t + \sqrt{1-\rho^2}z_t, \tag{20}$$

where $z_t \overset{\mathbb{P}}{\sim} \mathcal{N}(0,1)$ can be seen as a "pure-market" innovation process, independent from u_t. By construction, $\rho = \text{Corr}(\varepsilon_t, u_t)$ is the correlation between market returns and the innovations to the observable variable.[10] In the estimation of my model, the dynamics of x_t, and hence the u_ts, are assumed to be exogenous. Therefore, an estimate of ρ can be obtained simply by measuring the correlation between the filtered ε_ts and the u_ts.

Although inconsequential under the physical measure, this correlation has to be accounted for when the model is risk neutralized. My risk neutralization, building on CEFJ (2010), relies on the assumption that the risk premium on macroeconomic risk is subsumed by the equity risk premium and the contribution of macroeconomic conditions to the volatility process. This assumption is carried over to the model by maintaining λh_{t+1} as sole determinant of the risk premium in the expected return specification of equation (8). I show in Internet Appendix B that under this assumption, the correlation structure of equation (20) leads to the following risk neutralization of the macroeconomic and pure-market innovation processes:

$$\begin{aligned} u^*_t &= u_t + \rho\lambda, \\ z^*_t &= z_t + \sqrt{1-\rho^2}\lambda. \end{aligned}$$

[10] When considering a macroeconomic variable, this correlation structure implies that market movements do not feed back into the real economy; this implicit assumption is likely violated in practice (see, e.g., Bernanke, Gertler, and Gilchrist (1999) on the financial accelerator hypothesis) but is made here for the sake of simplicity. Corradi, Distaso, and Mele (2013) rely on a similar assumption in a continuous-time setting.

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The mean shift on each process is proportional to the correlation of that process with total market innovations. Interestingly, if $\rho = 0$, that is, if market shocks and macroeconomic shocks were uncorrelated, the latter would be unaffected by the risk neutralization.[11]

The risk-neutral form of the MacroGARCH model is therefore

$$R_{t+1} = r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon^*_{t+1}, \quad \text{where } \varepsilon^*_t = \rho u^*_t + \sqrt{1-\rho^2}z^*_t, \tag{21}$$

$$h_{t+1} = \tau_{t+1} + \alpha h_t\left(\varepsilon^*_t - 1 - 2\gamma^*\varepsilon^*_t\right) + \beta^*(h_t - \tau_t), \tag{22}$$

$$\tau_{t+1} = \left(1 + \theta\sum_{k=0}^{K-1}\phi_k(w)x_{t-k}\right)\sigma^{*2}. \tag{23}$$

This risk neutralization is not unique. In particular, it depends on the assumed correlation structure and the joint normality assumption. Recent work by Christoffersen, Heston, and Jacobs (2013) also demonstrates that deviating from the assumption that the Radon–Nikodym derivative is linear can greatly improve the option-valuation properties of a GARCH model. Hence, using this risk neutralization in the application that follows might very well underestimate the potential benefits of accounting for observables in option valuation.[12]

III. An Application Using Business Conditions

My framework allows me to depart from a paradigm that has been prevalent since Black and Scholes (1973) and consider the possibility that option values are partly determined by exogenous observable variables. Given the crucial link between volatility expectations and option prices, macroeconomic variables appear as natural candidates.

Theoretically, there are several channels through which uncertainty, volatility, and the real economy can be linked. In a consumption-based model, Bansal and Yaron (2004) find that fluctuating economic uncertainty can explain the volatility of market returns. Veldkamp and Wolfers (2007) argue that high fixed cost of information gathering might push firms to focus on cheap aggregate information, leading to production decisions overweighting aggregate shocks. In a real options framework, uncertainty directly affects investment decisions and can cause business cycles (Bernanke (1983), McDonald and Siegel (1986), and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014)).

Empirically, since Schwert (1989) showed that stock-market volatility is countercyclical, many studies have investigated the relation between business conditions and the volatility of stocks. Among many others, EGS (2013) estimate the MIDAS-GARCH using measures of inflation and of industrial production growth. From 1953 to 2004, they find that the level of these variables explains 35% and 17% of expected volatility, respectively. Engle and Rangel (2008) find the growth

[11] My risk neutralization presents similarities with that obtained by CFJM (2014) for their generalized affine realized volatility model. The main differences pertain to the fact that I assume that the observables are exogenous, whereas this obviously cannot be done with the realized volatility in CFJM.

[12] In particular, this can be highly relevant when considering variables that are informative about the variance risk premium (e.g., the VIX). I discuss the use of the VIX in Section IV.C.

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rate of real GDP to be an important determinant of stock market volatility.[13] David and Veronesi (2012) identify inflation and earnings uncertainty.

Studying how each of these variables affects option values would be an overwhelming task. Besides, although these variables are correlated, they all convey different pieces of information about the state of the economy. Individually, their impact on volatility and option prices might be limited. As stated by ADS ((2009), p. 417):

> Economic theory (e.g., Lucas, 1977) [...] emphasizes that the business cycle is not about any single variable, whether GDP, industrial production, sales, employment, or anything else. Rather, the business cycle is about the dynamics and interactions (co-movements) of many variables.

Consistent with this insight, Paye (2012) finds, using several macro-finance variables in linear predictive regressions, that volatility forecasts based on a single variable are often outperformed by a benchmark AR(2) volatility model. However, combining all the variables in a "kitchen sink" regression leads to consistently and significantly better forecasts than produced by the benchmark.

The MIDAS framework could straightforwardly accommodate the estimation of equation (10) with multiple macroeconomic series, but this would significantly increase the number of parameters in the models. Although complex models may better fit asset volatilities, option-based objective functions tend to favor relatively parsimonious models (Christoffersen and Jacobs (2004)).

Based on these considerations I prefer using a single variable, combining the information of many variables of interest in a timely fashion. The ADS business conditions index, built on the work of ADS (2009), is one such index. It was introduced on Jan. 9, 2009, by the Philadelphia Fed, and is conveniently updated as data on the index's underlying components are released.[14]

The ADS (2009) methodology is used to infer latent business conditions, in the spirit of Stock and Watson (1989), from the following six widely followed macroeconomic series released at different frequencies: weekly initial jobless claims (Init.Claims), monthly log-growth of nonagricultural payroll employment (Emp), industrial production (IP), real manufacturing and trade sales (Real MTS), real personal income minus transfers (Real Income), and quarterly real GDP (Real GDP). The ADS business conditions index is displayed in Graph A of Figure 1, with shaded regions highlighting recession periods, according to the dates published by the National Bureau of Economic Research (NBER).

The average value of the ADS index is 0, and progressively larger positive values indicate progressively better conditions. The converse is true for negative values. All deep troughs of the index coincide with NBER recessions. In that sense, the index clearly seems to adequately capture the relative quality level of business conditions over time. Note that although the NBER typically announces that the economy reached a peak or a trough several months after it actually oc-

[13] Engle and Rangel (2008) further identify measures of market development and other measures that are relevant in the context of their international analysis. My analysis is domestic only.

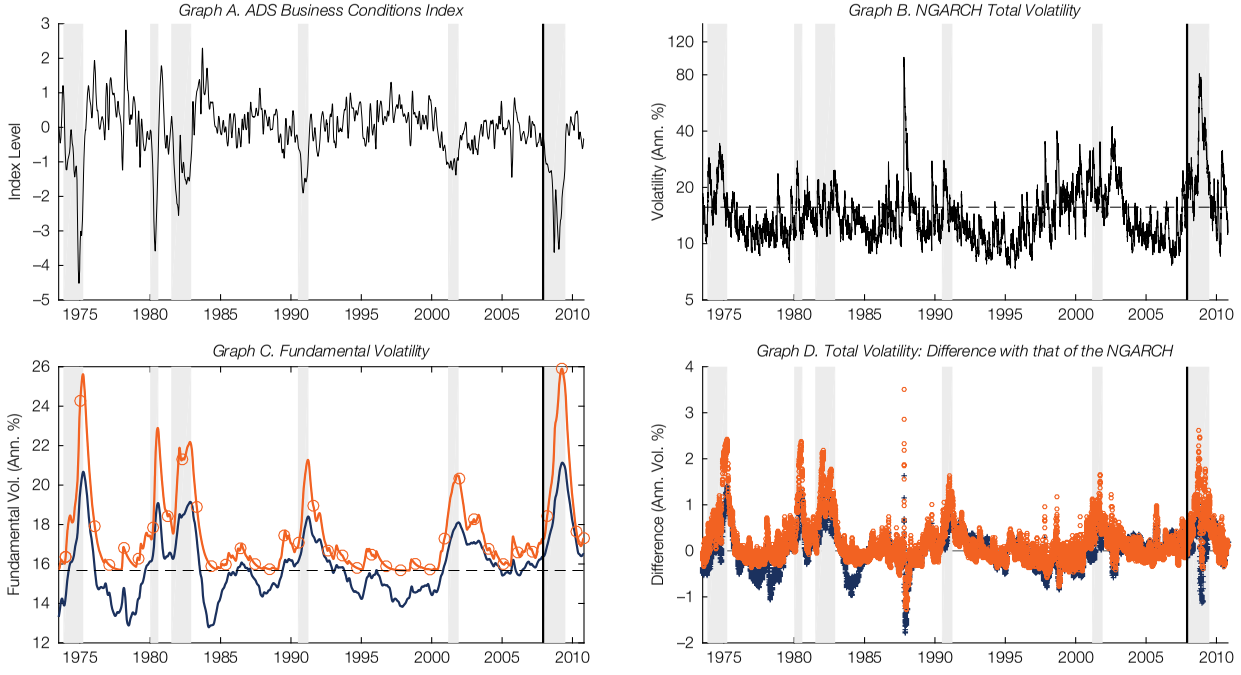
[14] Although the methodology behind the index leans heavily on ADS's (2009) work, the Fed modified it over time. A description of these changes can be found on the ADS index's Web page (https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index).

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FIGURE 1

Business Conditions and Volatility Processes

Graph A of Figure 1 plots the Aruoba–Diebold–Scotti (2009) (ADS) business conditions index over the estimation period and out of sample starting Dec. 1, 2007 (heavy vertical line). Gray-shaded regions highlight recessions dated by the National Bureau of Economic Research. Graph B plots the annualized volatility processes (in log scale) of the nonaffine generalized autoregressive conditional heteroskedasticity (NGARCH) model along with a dashed horizontal line at 15.7%, which corresponds to the NGARCH model's unconditional volatility. Graph C plots the annualized fundamental volatility level of the symmetric (dark line) and asymmetric (line with circles) MacroGARCH models. Graph D plots the difference between the annualized volatility of the MacroGARCH models and that of the nested NGARCH (symmetric: plus signs; asymmetric: circles).



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curred, the ADS index value is updated each time one of its input series is updated. For instance, the ADS index captured the U.S. economy's Dec. 2007 downturn in real time, whereas the NBER officially announced it 12 months later, on Dec. 1, 2008.

Correlations between the ADS business conditions index and its components, all (sub-) sampled at quarterly frequency, are reported in Table 1. When sampled at quarterly frequency, the ADS index is strongly correlated with its different components; the magnitude of the correlation ranges from 45.5% to 77.1%. The ADS index has the advantage of combining the informational content of its different components, sampled at different frequencies, into daily measures of business conditions. I consider the robustness of my results to this choice of variable in Section IV.

A. Model Estimation: Asset Returns and Stock Market Volatility

Taking the ADS business conditions index as an exogenous measure of business conditions, I estimate the MacroGARCH model given by equations (8)–(10) via maximum likelihood. Table 2 reports the estimates obtained using the S&P 500 returns between July 1973 and Nov. 2007 for the MacroGARCH model and for the nested NGARCH benchmark.[15] Results for the nested GARCH(1,1) model, without leverage effect ($\gamma = 0$), are also reported. Note that the estimation period ends before the most recent recession's official onset in Dec. 2007.

Consistent with the literature, a likelihood ratio test significantly favors, at any reasonable level, the NGARCH model over the GARCH(1,1) model. The same holds true when comparing the MacroGARCH model with its nested,

TABLE 1

Correlations between Macroeconomic Series Sampled Quarterly

Table 1 reports correlations between macroeconomic series sampled quarterly during the estimation period; the frequency at which each variable is available is in parentheses. The Aruoba–Diebold–Scotti (2009) (ADS) business conditions index, nonfarm payroll employment (Emp), industrial production index (IP), real personal income minus transfers (Real Income), and real gross domestic product data (Real GDP) were obtained from the Philadelphia Fed. The U.S. recessions probabilities (USRP) were obtained from the St. Louis Fed. Initial jobless claims (Init. Claims) and real manufacturing and trade sales (Real MTS) were obtained from EconStats.com. The ADS index is built on Init. Claims, Emp, IP, Real MTS, Real Income, and Real GDP. Following the Philadelphia Fed, I consider the log-growths of these series, except for Init. Claims, which are considered in levels. The maximum p-value associated with any of these correlations is 8.5E-5.

	USRP (monthly)	Init. Claims (weekly)	Emp (monthly)	IP (monthly)	Real MTS (monthly)	Real Income (monthly)	Real GDP (quarterly)
ADS	−0.7475	−0.4454	0.6899	0.7706	0.6822	0.5026	0.5601
USRP		0.6350	−0.6451	−0.6997	−0.6418	−0.4828	−0.5559
Init. Claims			−0.6349	−0.5121	−0.3282	−0.3814	−0.3973
Emp				0.7425	0.5557	0.5722	0.6793
IP					0.7027	0.5609	0.6649
Real MTS						0.5319	0.5783
Real Income							0.5540

[15] Note that returns between June 1969 and June 1973 are used to warm up the fundamental volatility process; however, the likelihood of these returns is disregarded. This study uses S&P 500 data because of their availability over a long horizon and because options on the S&P 500 have an extended history of being actively traded. Returns on major indexes and their volatility are usually highly correlated, and volatility tends to be higher in recessions regardless of the index considered. Thus, I am confident that the results obtained in this article would also be obtained using data from other stock indexes.

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TABLE 2
Maximum Likelihood Estimates

Table 2 reports maximum likelihood estimates for the generalized autoregressive conditional heteroskedasticity (GARCH(1,1)) and nonaffine GARCH (NGARCH) models and those of two specifications of the MacroGARCH model based on the Aruoba–Diebold–Scotti (2009) (ADS) business conditions index and an asymmetric version of the ADS index. Below each parameter estimate, I report its Bollerslev–Wooldridge (1992) standard error. The σ^2 parameter of all models is fixed at 9.75E-5, which corresponds to the 15.7% average volatility over the estimation sample. The p-value of likelihood ratio tests (LR p-value) is obtained benchmarking against the GARCH(1,1) for the NGARCH, and benchmarking against the NGARCH for the MacroGARCH specifications. Note that β is the persistence of the high-frequency volatility.

			MacroGARCH	
Parameters	GARCH(1,1)	NGARCH	Symmetric	Asymmetric
λ	0.0385 (5.28E-05)	0.0160 (1.38E-04)	0.0143 (6.39E-05)	0.0040 (6.03E-05)
α	0.0636 (2.01E-05)	0.0579 (3.18E-07)	0.0598 (3.64E-05)	0.0619 (6.37E-06)
β	0.9887 (1.73E-05)	0.9856 (1.15E-05)	0.9832 (2.12E-05)	0.9859 (5.54E-06)
γ		0.6901 (3.68E-04)	0.7093 (7.00E-04)	0.7202 (2.39E-04)
θ			−0.3827 (5.58E-06)	−0.7278 (6.98E-04)
w			6.0124 (8.84E-03)	8.3177 (1.40E-02)
Log-likelihood	28,702.9	28,783.7	28,791.4	28,793.5
LR p-value		0.000	0.000	0.000

$\gamma = 0$ variant (untabulated). A likelihood ratio test also significantly favors, at any reasonable level, the MacroGARCH model over the NGARCH model. Shared parameters have similar point estimates. Consistent with the countercyclicality of volatility, the θ parameter is negative. The estimate for w is such that at time t, x_{t-132} is given half the weight given to x_{t-1}. Graph B of Figure 1 reports the total volatility of the NGARCH model. If it were reported in the same panel, the total volatility of the MacroGARCH model would be visually indistinguishable from that of the NGARCH; the difference between the two is reported in Graph D.

Acknowledging that investors typically react asymmetrically to good and bad macroeconomic news (cf. Veronesi (1999)), I further consider a variant of the MacroGARCH model in which, rather than assuming $x_t = \text{ADS}_t$, I consider $x_t = \min(0, \text{ADS}_t)$, where ADS_t is the value of the business conditions index at time t. In this variant, the asymmetric MacroGARCH model, relatively poor business conditions directly increase fundamental variance. However, relatively good business conditions only indirectly lower fundamental variance by dissipating the contribution of past negative values of ADS_t. This asymmetric MacroGARCH model is strongly favored over the NGARCH model; the likelihood ratio test rejects the latter model at any reasonable level. Because of the asymmetric signal, the estimate for θ is almost twice as large in magnitude as that of the symmetric MacroGARCH. The asymmetric MacroGARCH's estimate for w is such that at time t, x_{t-92} is given half the weight given to x_{t-1}. Thus, the asymmetric MacroGARCH model allows deteriorating business conditions to have a greater and more immediate impact on fundamental volatility, as illustrated by Graphs C and D of Figure 1.

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B. Option Valuation

Accounting for business conditions in modeling the physical volatility process improves the model's ability to describe the past distribution of the volatility of returns. Next, I address whether accounting for business conditions helps to better describe the expected distribution volatility and thus improves the asset pricing properties of the MacroGARCH model on the cross section of option prices. I consider 21 years of call and put option prices from 1990 to 2010, one of the most extensive data sets in the option pricing literature. My data set covers three recessions: in early 1990, in 2001, and the recent 2007–2009 recession. Note that the models are estimated using asset returns series ending Nov. 2007, whereas the NBER has determined that the last recession started Dec. 2007. The last recession is thus treated fully out of sample.

1. Overall Results

Using the parameter estimates from Table 2 and the risk-neutralized form of the model, the evaluation of option prices via Monte Carlo is straightforward. I consider weekly cross sections of call and put options on the S&P 500 index from May 1990 to Oct. 2010. This data set is assembled from two databases: From May 1990 to Dec. 1995, I use option data obtained from the Chicago Mercantile Exchange group, and from Jan. 1996 to Oct. 2010, I use OptionMetrics data. All options were quoted on the CBOE.

The midpoint between bid and ask prices is used as the option price. Interest rates are downloaded from the Federal Reserve Board Data Releases. Dividends downloaded from the Center for Research in Security Prices are used to infer an ex-dividend index level to be used in the pricing of each option. I also filter zero-volume quotes and apply the filtering rules suggested by Bakshi, Cao, and Chen (1997) and discard options with more than 1 year to maturity. Note that I keep only out-of-the-money (OTM) options; thus, puts describe the left-hand side of the smile ($K/F \leq 1$), and calls describe the right-hand side ($K/F \geq 1$). Overall, this leaves 110,237 observations.

For each model, I perform Monte Carlo simulations on each Wednesday t_w, using 100,000 paths of $\{\varepsilon^*_{t_w+\tau,k}\}$ to price options quoted in week t_w. The shocks are generated using Sobol sequences and I perform the empirical martingale adjustment of Duan and Simonato (1998), which ensures that each simulated path has a drift of r.[16]

For any subsample of options, the time series of weekly relative root mean squared error, $\%\text{RMSE}_w$, and implied-volatility root mean squared error, IVRMSE_w, can be computed by considering option prices observed during week w:

[16] Precisely, I use 20 affine matrix scrambles of 5,000 Sobol sequences each, for a total of 100,000 simulated paths. CDJW (2010) illustrate the accuracy of these simulation settings by comparing the quasi–Monte Carlo results with the exact results computed with the quasi-analytical solutions for the affine model of Heston and Nandi (2000).

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$$\%\text{RMSE}_w = \frac{\$\text{RMSE}_w}{\overline{V}_w}, \tag{24}$$

where

$$\$\text{RMSE}_w = \sqrt{\frac{1}{N}\sum_k \left(V_{w,k} - V_{w,k}^{\text{MODEL}}\right)^2},$$

$$\text{IVRMSE}_w = \sqrt{\frac{1}{N}\sum_k \left(\text{IV}_{w,k} - \text{IV}_{w,k}^{\text{MODEL}}\right)^2}, \tag{25}$$

where $\text{IV}_{w,k}$ is the implied volatility given the market value $V_{w,k}$ of option k at time w, $\text{IV}_{w,k}^{\text{MODEL}}$ is the implied volatility obtained from the model price $V_{w,k}^{\text{MODEL}}$, and $\overline{V}_w$ is the weekly average price of options in the sample under consideration. The implied volatility is obtained by inverting the Black–Merton–Scholes formula (Black and Scholes (1973), Merton (1973), (1974)), which simply serves as a bijection between the price domain and the volatility domain. The %RMSE metric, obtained in the price domain, and the IVRMSE metric, obtained in the implied volatility domain, both convey useful information. Whereas %RMSE is directly linked to the economic significance of the pricing errors, IVRMSE provides a more robust measure of the goodness of fit of an option-valuation model (see Renault (1997)). As my focus is on the economic significance of accounting on business conditions, I mainly discuss the %RMSE results. The IVRMSE results are reported for completeness and strongly support the %RMSE results.

Table 3 reports, in percentage points, average %RMSE and IVRMSE for the whole sample (e.g., $\sum_{w=1}^{1,070} \%\text{RMSE}_w/1{,}070$) and for different subsamples of options divided along maturity, option type (put or call), and moneyness (K/F). For each subsample, Table 3 also reports t-statistics (in parentheses) on the average of

$$\%\text{RMSE}_w^{\mathcal{M}} - \%\text{RMSE}_w^{\text{asymmetric MacroGARCH}}$$

and

$$\text{IVRMSE}_w^{\mathcal{M}} - \text{IVRMSE}_w^{\text{asymmetric MacroGARCH}}$$

to assess whether model $\mathcal{M}$ is significantly outperformed by the asymmetric MacroGARCH model. Negative t-statistics would arise when $\mathcal{M}$ dominates, which is never the case in Table 3.

Finally, I report the ratio of the model's pricing error to that of the asymmetric MacroGARCH model. For the NGARCH, along the maturity dimension, this %RMSE ratio varies from 1.04 for short-term options to 1.08 for long-term options, indicating that the pricing errors of the asymmetric MacroGARCH model are from 4% to 8% smaller than the errors of the NGARCH model. Along the moneyness dimension, the average improvement ranges from 7% for OTM puts to 8% for OTM calls. In all cases, the differences are statistically and economically significant.

Note that the symmetric MacroGARCH model also improves on the NGARCH model in all subsamples of options, although much more modestly. These results further support the asset-returns results and, consistent with the literature (cf. Veronesi (1999)), further document the asymmetric reaction of stock

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TABLE 3
Option-Pricing Results: Whole Sample (May 1990–Oct. 2010)

For any subsample of options, the time series of weekly relative root mean squared error (%RMSE$_w$) and implied-volatility root mean squared error (IVRMSE$_w$) can be computed by considering option prices observed during week w, as per equations (24) and (25). Table 3 reports, in percentage points, the average %RMSE and IVRMSE (e.g., Σ_w%RMSE$_w$/1,070) for the whole sample and for various subsamples of options. For each subsample, I also report t-statistics (in parentheses) on the average of $\%\text{RMSE}_w^{\mathcal{M}} - \%\text{RMSE}_w^{\text{AMG}}$ and $\text{IVRMSE}_w^{\mathcal{M}} - \text{IVRMSE}_w^{\text{AMG}}$, to assess whether model $\mathcal{M}$ is significantly outperformed by the asymmetric MacroGARCH model (amg); negative t-statistics arise when $\mathcal{M}$ dominates. The t-statistics are computed using Newey–West (1994) standard errors with a lag of 12 weeks and are bold whenever their magnitude is larger than 1.96. The choice of a quarter-long lag is arbitrary and intended to be conservative; in my case, $T = 1{,}070$ such that $[4(T/100)^{0.25}] = 7$ weeks would be the lag suggested by Newey and West. Additionally, I report the ratio (in square brackets) of the model's pricing error to that of the Aruoba–Diebold–Scotti (2009) (ADS)-based asymmetric MacroGARCH model. GARCH stands for generalized autoregressive conditional heteroskedasticity, NGARCH stands for nonaffine GARCH, OTM stands for out of the money, and ATM stands for at the money.

	%RMSE				IVRMSE			
			MacroGARCH				MacroGARCH	
	GARCH(1,1)	NGARCH	Symmetric	Asymmetric	GARCH(1,1)	NGARCH	Symmetric	Asymmetric
All options	41.12	36.45	35.29	33.89	5.86	4.61	4.49	4.33
	(9.46)	**(3.58)**	**(4.31)**	–	**(16.53)**	**(4.70)**	**(5.44)**	–
	[1.21]	[1.08]	[1.04]	[1.00]	[1.35]	[1.06]	[1.04]	[1.00]
Maturity								
Short term	37.79	34.00	33.37	32.77	5.81	4.75	4.63	4.52
	(7.47)	**(3.51)**	**(3.13)**	–	**(13.42)**	**(5.71)**	**(4.87)**	–
	[1.15]	[1.04]	[1.02]	[1.00]	[1.29]	[1.05]	[1.02]	[1.00]
Medium term	36.56	32.28	31.64	30.74	5.72	4.47	4.38	4.23
	(8.95)	**(3.40)**	**(3.83)**	–	**(15.69)**	**(4.42)**	**(5.05)**	–
	[1.19]	[1.05]	[1.03]	[1.00]	[1.35]	[1.06]	[1.04]	[1.00]
Long term	36.09	31.77	30.73	29.30	5.76	4.37	4.26	4.02
	(9.21)	**(3.49)**	**(4.50)**	–	**(15.99)**	**(3.91)**	**(5.71)**	–
	[1.23]	[1.08]	[1.05]	[1.00]	[1.43]	[1.09]	[1.06]	[1.00]
Calls								
All	32.43	33.69	32.40	31.00	2.71	2.77	2.68	2.60
	(1.59)	**(3.26)**	**(3.43)**	–	(1.11)	**(2.63)**	**(2.52)**	–
	[1.05]	[1.09]	[1.05]	[1.00]	[1.04]	[1.06]	[1.03]	[1.00]
ATM	21.51	22.61	21.83	20.97	2.79	2.89	2.79	2.70
	(0.91)	**(3.23)**	**(3.39)**	–	(1.26)	**(2.91)**	**(3.13)**	–
	[1.03]	[1.08]	[1.04]	[1.00]	[1.04]	[1.07]	[1.04]	[1.00]
OTM	43.02	44.61	43.26	41.24	2.65	2.74	2.66	2.58
	(1.37)	**(3.14)**	**(3.49)**	–	(0.62)	**(2.45)**	**(2.44)**	–
	[1.04]	[1.08]	[1.05]	[1.00]	[1.03]	[1.06]	[1.03]	[1.00]
Puts								
All	43.73	36.77	35.59	34.25	6.90	5.24	5.12	4.91
	(11.37)	**(3.63)**	**(4.26)**	–	**(17.66)**	**(5.18)**	**(5.96)**	–
	[1.28]	[1.07]	[1.04]	[1.00]	[1.40]	[1.07]	[1.04]	[1.00]
ATM	21.95	21.38	20.69	19.98	3.32	3.19	3.10	3.00
	(3.32)	**(3.10)**	**(3.13)**	–	**(3.97)**	**(3.00)**	**(3.26)**	–
	[1.10]	[1.07]	[1.04]	[1.00]	[1.11]	[1.06]	[1.03]	[1.00]
OTM	54.16	43.67	42.26	40.66	7.43	5.56	5.42	5.20
	(13.78)	**(3.74)**	**(4.38)**	–	**(19.63)**	**(5.42)**	**(6.15)**	–
	[1.33]	[1.07]	[1.04]	[1.00]	[1.43]	[1.07]	[1.04]	[1.00]

market volatility to changes in macroeconomic conditions. Note that this asymmetric reaction complements the asymmetry introduced by the leverage parameter γ, which, in line with the literature, plays a crucial role in better describing the left-hand side of the smile.

2. Estimation Period and Out-of-Sample Results

I perform simulations using only the information set up to time t_w with the notable exception that I use parameter estimates from Table 2, estimated using the S&P 500 return series ending in Nov. 2007. When these parameter estimates are used to price options between May 1990 and Nov. 2007, this is not strictly

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out of sample. Given that the models are estimated without using option data, this exercise is still stringent in terms of analyzing a model's capacity to properly describe the expected distribution of future returns. I nonetheless refer to this subsample of options as being from the estimation period. Table 4 summarizes the results obtained for the subsample of options quoted during the estimation period (73,957 observations), whereas Table 5 summarizes those obtained on the subsample of options quoted after the estimation period, which I refer to as out of sample (36,280 observations). Note that the NBER determined that the Great Recession began in Dec. 2007 and ended in June 2009. This recession is thus treated fully out of sample and covers most of the out-of-sample period.

For all models, the pricing errors are systematically larger out of sample than in the estimation period, as expected. Interestingly, however, the improvements

TABLE 4

Option-Pricing Results: Estimation Period Only (May 1990–Nov. 2007)

In the spirit of Table 3, Table 4 reports, in percentage points, the average root mean squared error (%RMSE) and implied-volatility root mean squared error (IVRMSE) (e.g., Σ_w%RMSE$_w$/918) for various subsamples of options between May 1990 and Nov. 2007. The asymmetric MacroGARCH model significantly outperforms a model over a given subsample whenever the t-statistic (in parentheses) is positive and bold. I also report the ratio (in square brackets) of the model's pricing error to that of the Aruoba–Diebold–Scotti (2009) (ADS)-based asymmetric MacroGARCH model. GARCH stands for generalized autoregressive conditional heteroskedasticity, NGARCH stands for nonaffine GARCH, OTM stands for out of the money, and ATM stands for at the money.

	%RMSE				IVRMSE			
			MacroGARCH				MacroGARCH	
	GARCH(1,1)	NGARCH	Symmetric	Asymmetric	GARCH(1,1)	NGARCH	Symmetric	Asymmetric
All options	38.64	33.45	33.30	32.14	5.27	4.12	4.08	3.95
	(8.03)	**(2.16)**	**(3.87)**	–	**(16.68)**	**(3.66)**	**(5.65)**	–
	[1.20]	[1.04]	[1.04]	[1.00]	[1.34]	[1.04]	[1.03]	[1.00]
Maturity								
Short term	36.88	32.97	32.78	32.12	5.26	4.31	4.24	4.14
	(6.60)	**(2.55)**	**(3.50)**	–	**(12.61)**	**(4.79)**	**(5.12)**	–
	[1.15]	[1.03]	[1.02]	[1.00]	[1.27]	[1.04]	[1.02]	[1.00]
Medium term	35.18	30.53	30.51	29.70	5.14	4.01	3.98	3.86
	(7.59)	**(2.09)**	**(3.68)**	–	**(15.56)**	**(3.39)**	**(5.46)**	–
	[1.18]	[1.03]	[1.03]	[1.00]	[1.33]	[1.04]	[1.03]	[1.00]
Long term	33.76	28.95	28.89	27.70	5.08	3.78	3.79	3.60
	(7.87)	**(2.06)**	**(4.01)**	–	**(17.36)**	**(2.67)**	**(5.99)**	–
	[1.22]	[1.04]	[1.04]	[1.00]	[1.41]	[1.05]	[1.05]	[1.00]
Calls								
All	30.64	31.31	31.28	30.05	2.43	2.49	2.50	2.42
	(0.62)	(1.80)	**(3.11)**	–	(0.04)	(1.41)	**(3.44)**	–
	[1.02]	[1.04]	[1.04]	[1.00]	[1.00]	[1.03]	[1.03]	[1.00]
ATM	20.41	21.28	21.22	20.49	2.51	2.56	2.57	2.49
	(−0.13)	(1.78)	**(2.90)**	–	(0.27)	(1.57)	**(3.49)**	–
	[1.00]	[1.04]	[1.04]	[1.00]	[1.01]	[1.03]	[1.03]	[1.00]
OTM	41.87	42.50	42.81	40.90	2.38	2.48	2.50	2.42
	(0.68)	(1.68)	**(3.21)**	–	(−0.35)	(1.24)	**(3.52)**	–
	[1.02]	[1.04]	[1.05]	[1.00]	[0.98]	[1.03]	[1.03]	[1.00]
Puts								
All	40.70	33.26	32.97	31.94	6.22	4.68	4.63	4.47
	(9.92)	**(2.21)**	**(3.53)**	–	**(17.39)**	**(4.03)**	**(5.55)**	–
	[1.27]	[1.04]	[1.03]	[1.00]	[1.39]	[1.05]	[1.04]	[1.00]
ATM	20.71	19.89	19.81	19.24	3.01	2.83	2.83	2.75
	(2.29)	(1.62)	**(2.55)**	–	**(2.89)**	(1.62)	**(3.33)**	–
	[1.08]	[1.03]	[1.03]	[1.00]	[1.09]	[1.03]	[1.03]	[1.00]
OTM	50.85	39.64	39.18	37.96	6.75	4.99	4.93	4.75
	(12.22)	**(2.33)**	**(3.57)**	–	**(19.42)**	**(4.26)**	**(5.64)**	–
	[1.34]	[1.04]	[1.03]	[1.00]	[1.42]	[1.05]	[1.04]	[1.00]

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TABLE 5
Option-Pricing Results: Out of Sample (Dec. 2007–Oct. 2010)

Similar to Table 3, Table 5 reports, in percentage points, the average root mean squared error (%RMSE) and implied-volatility root mean squared error (IVRMSE) (e.g., Σ_w %RMSE$_w$/152) for various subsamples of options between Dec. 2007 and Oct. 2010. The asymmetric MacroGARCH model significantly outperforms a model over a given subsample whenever the t-statistic (in parentheses) is positive and bold. I also report the ratio (in square brackets) of the model's pricing error to that of the Aruoba–Diebold–Scotti (2009) (ADS)-based asymmetric MacroGARCH model. GARCH stands for generalized autoregressive conditional heteroskedasticity, NGARCH stands for nonaffine GARCH, OTM stands for out of the money, and ATM stands for at the money.

	%RMSE				IVRMSE			
			MacroGARCH				MacroGARCH	
	GARCH(1,1)	NGARCH	Symmetric	Asymmetric	GARCH(1,1)	NGARCH	Symmetric	Asymmetric
All options	56.11	54.60	47.28	44.44	9.42	7.55	6.97	6.66
	(6.93)	**(4.25)**	**(2.18)**	–	**(15.99)**	**(4.11)**	**(2.22)**	–
	[1.26]	[1.23]	[1.06]	[1.00]	[1.41]	[1.13]	[1.05]	[1.00]
Maturity								
Short term	43.26	40.22	36.97	36.64	9.18	7.40	6.97	6.82
	(3.81)	**(2.91)**	(0.43)	–	**(10.96)**	**(4.18)**	(1.56)	–
	[1.18]	[1.10]	[1.01]	[1.00]	[1.35]	[1.09]	[1.02]	[1.00]
Medium term	44.55	42.45	38.18	36.80	9.06	7.19	6.70	6.41
	(6.36)	**(3.73)**	(1.49)	–	**(13.63)**	**(3.83)**	(1.98)	–
	[1.21]	[1.15]	[1.04]	[1.00]	[1.41]	[1.12]	[1.04]	[1.00]
Long term	50.16	48.86	41.87	38.96	9.86	7.94	7.12	6.57
	(6.38)	**(4.24)**	**(2.33)**	–	**(12.87)**	**(4.03)**	**(2.73)**	–
	[1.29]	[1.25]	[1.07]	[1.00]	[1.50]	[1.21]	[1.08]	[1.00]
Calls								
All	43.19	47.95	39.09	36.68	4.44	4.45	3.75	3.70
	(3.26)	**(4.07)**	(1.56)	–	**(2.28)**	**(2.80)**	(0.33)	–
	[1.18]	[1.31]	[1.07]	[1.00]	[1.20]	[1.20]	[1.01]	[1.00]
ATM	28.06	30.56	25.46	23.87	4.52	4.82	4.17	3.97
	(3.37)	**(4.15)**	(1.84)	–	**(3.34)**	**(3.28)**	(1.22)	–
	[1.18]	[1.28]	[1.07]	[1.00]	[1.14]	[1.21]	[1.05]	[1.00]
OTM	49.88	57.19	45.93	43.26	4.25	4.29	3.58	3.56
	(2.62)	**(4.09)**	(1.41)	–	(1.94)	**(2.66)**	(0.13)	–
	[1.15]	[1.32]	[1.06]	[1.00]	[1.19]	[1.21]	[1.01]	[1.00]
Puts								
All	61.99	57.92	51.43	48.20	11.00	8.64	8.08	7.60
	(7.02)	**(4.38)**	**(2.70)**	–	**(16.70)**	**(4.90)**	**(3.37)**	–
	[1.29]	[1.20]	[1.07]	[1.00]	[1.45]	[1.14]	[1.06]	[1.00]
ATM	29.42	30.37	25.99	24.46	5.24	5.35	4.74	4.49
	(4.35)	**(4.21)**	(1.94)	–	**(4.47)**	**(3.48)**	(1.50)	–
	[1.20]	[1.24]	[1.06]	[1.00]	[1.17]	[1.19]	[1.05]	[1.00]
OTM	74.18	67.97	60.83	56.97	11.52	8.96	8.40	7.89
	(7.41)	**(4.49)**	**(2.93)**	–	**(17.51)**	**(5.07)**	**(3.56)**	–
	[1.30]	[1.19]	[1.07]	[1.00]	[1.46]	[1.14]	[1.06]	[1.00]

obtained using the asymmetric MacroGARCH are much larger out of sample than during the estimation period.

Table 5 reports that, along the maturity dimension, the asymmetric MacroGARCH model yields improvements over the NGARCH model ranging from 10% for short-term options to 25% for long-term options. Along the moneyness dimension, improvements range from 19% for OTM puts to 32% for OTM calls. In all cases, the differences are statistically and economically significant.

Thus, in relative terms, it seems that the asymmetric MacroGARCH performs even better out of sample than during the estimation period. Although this result is relatively uncommon, it is undoubtedly driven by the nature of the out-of-sample period, which mainly consists of one of the deepest recessions in history and its aftermath.

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3. Improved Option Valuation When Business Conditions Deteriorate

Overall, my data set covers three recessions: the first in the early 1990s, the second in 2001, and the recent 2007–2009 recession. Table 6 focuses on the option-pricing errors observed during these three recessions.

Pricing error ratios in Table 6 show that during recessions, the asymmetric MacroGARCH pricing errors are between 15% and 42% smaller than those of the NGARCH. The improvement increases with option maturity (from 15% to 38%), and from the left to the right of the smile (from 30% for OTM puts to 42% for OTM calls). Note that absolute rather than relative measures of improvements are U-shaped; absolute improvements are much larger OTM than ATM. On average, the pricing errors of the asymmetric MacroGARCH are 33% lower than those of the benchmark NGARCH model. In comparison, Table 3 reports an average

TABLE 6

Option-Pricing Results: Recessions Only
(July 1990–Mar. 1991, Mar. 2001–Nov. 2001, and Dec. 2007–June 2009)

Similar to Table 3, Table 6 reports, in percentage points, the average root mean squared error (%RMSE) and implied-volatility root mean squared error (IVRMSE) (e.g., Σ_w %RMSE$_w$/148) during recessions for various subsamples of options. The asymmetric MacroGARCH model significantly outperforms a model over a given subsample whenever the *t*-statistic (in parentheses) is positive and bold. I also report the ratio (in square brackets) of the model's pricing error to that of the Aruoba–Diebold–Scotti (2009) (ADS)-based asymmetric MacroGARCH model. GARCH stands for generalized autoregressive conditional heteroskedasticity, NGARCH stands for nonaffine GARCH, OTM stands for out of the money, and ATM stands for at the money.

	%RMSE				IVRMSE			
			MacroGARCH				MacroGARCH	
	GARCH(1,1)	NGARCH	Symmetric	Asymmetric	GARCH(1,1)	NGARCH	Symmetric	Asymmetric
All options	44.77	41.28	35.50	31.08	7.71	6.09	5.61	5.16
	(10.02)	**(6.26)**	**(4.60)**	–	**(15.29)**	**(5.72)**	**(3.79)**	–
	[1.44]	[1.33]	[1.14]	[1.00]	[1.49]	[1.18]	[1.09]	[1.00]
Maturity								
Short term	39.30	33.33	30.71	28.92	7.97	6.21	5.85	5.55
	(7.74)	**(4.08)**	**(2.55)**	–	**(11.63)**	**(5.37)**	**(3.32)**	–
	[1.36]	[1.15]	[1.06]	[1.00]	[1.44]	[1.12]	[1.05]	[1.00]
Medium term	38.79	33.72	30.49	27.68	7.53	5.77	5.37	4.95
	(8.51)	**(5.25)**	**(3.54)**	–	**(12.20)**	**(5.02)**	**(3.08)**	–
	[1.40]	[1.22]	[1.10]	[1.00]	[1.52]	[1.17]	[1.08]	[1.00]
Long term	39.83	36.92	31.18	26.77	7.23	5.90	5.22	4.52
	(9.96)	**(6.34)**	**(4.70)**	–	**(16.07)**	**(5.60)**	**(4.24)**	–
	[1.49]	[1.38]	[1.16]	[1.00]	[1.60]	[1.31]	[1.16]	[1.00]
Calls								
All	35.05	37.37	30.50	26.48	4.15	3.89	3.34	3.13
	(5.39)	**(5.45)**	**(3.25)**	–	**(3.94)**	**(3.79)**	(1.46)	–
	[1.32]	[1.41]	[1.15]	[1.00]	[1.33]	[1.24]	[1.07]	[1.00]
ATM	22.65	23.85	19.92	17.20	4.15	4.17	3.65	3.28
	(5.02)	**(6.35)**	**(4.45)**	–	**(5.73)**	**(4.67)**	**(2.64)**	–
	[1.32]	[1.39]	[1.16]	[1.00]	[1.27]	[1.27]	[1.11]	[1.00]
OTM	39.97	44.02	35.44	30.92	3.99	3.74	3.19	3.02
	(4.39)	**(5.09)**	**(2.80)**	–	**(3.39)**	**(3.50)**	(1.17)	–
	[1.29]	[1.42]	[1.15]	[1.00]	[1.32]	[1.24]	[1.06]	[1.00]
Puts								
All	47.73	42.23	37.08	32.25	8.99	6.94	6.47	5.83
	(8.88)	**(6.70)**	**(6.05)**	–	**(16.48)**	**(7.12)**	**(6.06)**	–
	[1.48]	[1.31]	[1.15]	[1.00]	[1.54]	[1.19]	[1.11]	[1.00]
ATM	24.33	23.92	20.41	17.85	4.86	4.64	4.15	3.74
	(5.40)	**(5.87)**	**(4.16)**	–	**(6.18)**	**(4.86)**	**(2.97)**	–
	[1.36]	[1.34]	[1.14]	[1.00]	[1.30]	[1.24]	[1.11]	[1.00]
OTM	57.53	49.78	43.94	38.15	9.49	7.25	6.77	6.09
	(9.02)	**(6.91)**	**(6.80)**	–	**(17.50)**	**(7.43)**	**(6.58)**	–
	[1.51]	[1.30]	[1.15]	[1.00]	[1.56]	[1.19]	[1.11]	[1.00]

8% improvement. Clearly, most of the improvement arises from better describing volatility expectations around recessions. These results are consistent with those of Paye (2012), who finds that the predictive power associated with macroeconomic variables concentrates around recessions.

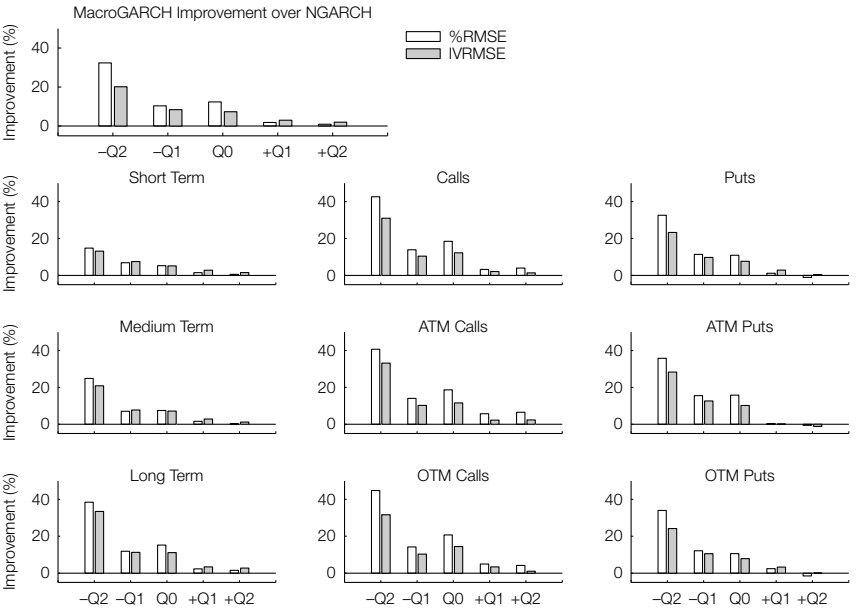
Performance ratios in Table 6 emphasize that although the symmetric MacroGARCH model systematically outperforms the NGARCH model in recessions, it is in turn significantly outperformed by the asymmetric version of the model. As discussed in the estimation of parameters, the loading of the symmetric model's fundamental volatility on business conditions is much smaller, $\theta = -0.3827$, than that of its asymmetric counterpart, $\theta = -0.7278$. My option-pricing results strongly favor the asymmetric model and thus support the hypothesis that deteriorating business conditions increase financial volatility to a greater extent than improving conditions lower it.

Figure 2 details how the improvement of the asymmetric MacroGARCH over the NGARCH is related to the prevailing business conditions. I first obtain the quintiles of the ADS business conditions index values for the weeks during the option-valuation period. The relative weekly pricing errors, $\$\text{RMSE}_w^{\mathcal{M}}/\$\text{RMSE}_w^{\text{AMG}}$, where AMG stands for asymmetric MacroGARCH, are

FIGURE 2

The Impact of Accounting for Changes in Business Conditions

Figure 2 reports the average relative pricing improvements obtained using the MacroGARCH model instead of the nonaffine generalized autoregressive conditional heteroskedasticity (NGARCH) model. The data are divided into five buckets corresponding to the quintiles of the Aruoba–Diebold–Scotti (2009) (ADS) business conditions index (x_t). In −Q2, business conditions are at their worst, whereas in +Q2, they are at their best. For each quintile, I average the root mean squared error (RMSE) ratios (cf. Table 3) obtained for each week in the quintile, and I report the average ratio (minus 1) of the NGARCH model. Short-term options have between 6 and 45 days to maturity (DTM), and long-term options have between 92 and 365 DTM. For out-of-the-money (OTM) puts, $K/F \leq 0{:}975$; for OTM calls, $K/F \geq 1{:}025$. IVRMSE stands for implied-volatility root mean squared error, and ATM stands for at the money.



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then averaged in the five buckets obtained by the quintiles. When the ADS index is in its lowest quintile, labeled −Q2, it reflects increasing initial jobless claims and negative growth of employment, industrial production, real manufacturing and trade sales, real income, and real GDP. In short, −Q2 regroups the 214 weeks in my sample in which business conditions are at their worst. Conversely, the highest quintile, +Q2, regroups the 214 weeks in which business conditions are at their best. Figure 2 shows that the asymmetric MacroGARCH model improves on the NGARCH model in a clearly countercyclical manner.

IV. Alternative Model Specifications

A. Component Model Specifications

The MacroGARCH model allows for two volatility components: the fundamental volatility and a high-frequency volatility component that varies around the fundamental volatility. The finding that such models better describe stock market volatility and option prices is consistent with the growing consensus that 2-factor volatility processes more effectively capture the time-series properties of volatility by separately accounting for transient and highly persistent volatility shocks.

Hence, it is important to assess whether the improvements offered by the MacroGARCH model truly arise from accounting for business conditions. A legitimate concern is that the fundamental volatility of the MacroGARCH could merely proxy for the low-frequency component of, for example, the component NGARCH model of Engle and Lee (1999), studied by CDJW (2010):

$$h_{t+1} = q_{t+1} + \alpha_1 h_t \left(\varepsilon_t^2 - 1 - 2\gamma_1\varepsilon_t\right) + \beta_1(h_t - q_t), \tag{26}$$

$$q_{t+1} = \sigma^2 + \alpha_2 h_t \left(\varepsilon_t^2 - 1 - 2\gamma_2\varepsilon_t\right) + \beta_2(q_t - \sigma^2). \tag{27}$$

I refer to this model as the NGARCH(C) model.

As illustrated by Figure 3, the fundamental volatility process of the MacroGARCH model and the low-frequency volatility process of equation (27) appear to play fundamentally different roles. The latter is a virtually latent autoregressive process that simply provides the model with more flexibility to explain the long-memory-like properties of volatility.[17] The fundamental volatility process, conversely, captures slowly evolving expectations. This suggests that both the low-frequency and fundamental volatilities could be used in conjunction.

Consequently, inspired by the work on multifrequency news and volatility by Calvet and Fisher (2001), (2002), (2003), and (2007), I suggest the following model:

$$h_{t+1} = q_{t+1} + \alpha_1 h_t \left(\varepsilon_t^2 - 1 - 2\gamma_1\varepsilon_t\right) + \beta_1(h_t - q_t), \tag{28}$$

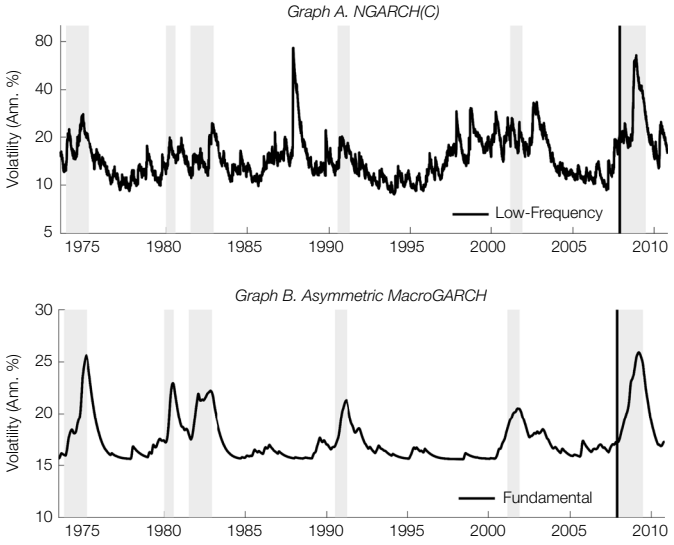
$$q_{t+1} = \tau_{t+1} + \alpha_2 h_t \left(\varepsilon_t^2 - 1 - 2\gamma_2\varepsilon_t\right) + \beta_2(q_t - \tau_t), \tag{29}$$

$$\tau_{t+1} = \left(1 + \theta \sum_{k=0}^{K-1} \phi_k(w) x_{t-k}\right)\sigma^2, \tag{30}$$

[17] In a GARCH framework, the volatility process is not actually latent but is an estimate of a conceptually latent process.

FIGURE 3
Low-Frequency and Fundamental Volatility Processes

Graph A of Figure 3 plots (in log scale) the low-frequency volatility component of a 2-component nonaffine generalized autoregressive conditional heteroskedasticity (NGARCH(C)) model estimated using S&P 500 returns between July 1973 and Nov. 2007. Graph B plots the fundamental volatility component of the asymmetric MacroGARCH model estimated using the same data. Gray-shaded regions highlight recessions dated by the National Bureau of Economic Research.



which I refer to as the MacroGARCH(C) model. This model thus has three volatility components: a high-frequency volatility component, which evolves around a low-frequency volatility component, which in turn evolves around time-varying volatility expectations described by the fundamental volatility process.

Tables 7 and 8 compare the option-valuation errors of the NGARCH(C) and asymmetric MacroGARCH(C) models.[18] These tables further report results for the NGARCH(C_3), a model in which the third volatility component is purely autoregressive,

$$\tau_{t+1} = \sigma^2 + \alpha_3 h_t \left(\varepsilon_t^2 - 1 - 2\gamma_3\varepsilon_t\right) + \beta_3(q_t - \tau_t), \tag{31}$$

and does not load on the business conditions index.

First, during the estimation period, comparing Table 7 with Table 4 shows that the NGARCH(C) yields an average improvement of 5% over the NGARCH. Out of sample, comparing Table 8 with Table 5, the average improvement is 28%. My results support the results of CDJW (2010): The option-valuation performance of the NGARCH(C) model is superior to that of the NGARCH. Adding a low-frequency component also improves the asymmetric MacroGARCH. During the estimation period, the two-component version of the model is 7% better than the single-component version; out of sample, this figure increases to 23%. It thus

[18]The models' parameters are estimated following the procedure described in Section III.A. Estimates are not reported but are available from the author. The risk-neutralized form of the models are provided in the Internet Appendix.

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TABLE 7

Option-Pricing Results: Alternative Specifications
(Estimation Period, May 1990–Nov. 2007)

The models considered in Table 7 all nest the NGARCH(C) model. Similar to Table 4, Table 7 reports, in percentage points, the average root mean squared error (%RMSE) for various subsamples of options during the estimation period. For each subsample, I also report t-statistics (in parentheses) on the average of $\%\text{RMSE}_w^{\mathcal{M}} - \%\text{RMSE}_w^{\text{AMGC}}$ to assess whether model $\mathcal{M}$ is significantly outperformed by the asymmetric MacroGARCH(C) model ($_{\text{AMG}}$(c)); negative t-statistics arise when $\mathcal{M}$ dominates. The t-statistics are computed using Newey–West (1994) standard errors with a lag of 12 weeks and are bold whenever their magnitude is larger than 1.96. Additionally, I report the ratio (in square brackets) of the model's pricing error to that of the Aruoba–Diebold–Scotti (2009) (ADS)-based asymmetric MacroGARCH(C) model. GARCH stands for generalized autoregressive conditional heteroskedasticity, NGARCH stands for nonaffine GARCH, OTM stands for out of the money, and ATM stands for at the money. The corresponding implied-volatility root mean squared error results are reported in Table IA.1 in the Internet Appendix.

	%RMSE				
			MacroGARCH(C)		
	NGARCH(C)	NGARCH(C_3)	Rec. Prob.	VIX	Asym. ADS
All options	31.97	31.14	31.30	28.10	30.07
	(4.83)	**(2.43)**	**(5.26)**	(−1.43)	–
	[1.06]	[1.04]	[1.04]	[0.93]	[1.00]
Maturity					
Short term	28.38	27.98	27.77	25.21	27.48
	(4.23)	(1.79)	(1.97)	**(−2.38)**	–
	[1.03]	[1.02]	[1.01]	[0.92]	[1.00]
Medium term	27.85	27.04	27.19	23.55	26.68
	(5.02)	(1.26)	**(3.06)**	**(−2.76)**	–
	[1.04]	[1.01]	[1.02]	[0.88]	[1.00]
Long term	28.31	27.55	27.75	24.85	26.47
	(4.70)	**(2.49)**	**(5.65)**	(−1.17)	–
	[1.07]	[1.04]	[1.05]	[0.94]	[1.00]
Calls					
All	24.10	23.47	23.32	27.52	22.93
	(2.44)	(1.07)	(1.51)	**(3.63)**	–
	[1.05]	[1.02]	[1.02]	[1.20]	[1.00]
ATM	17.28	16.77	16.73	17.58	16.30
	(3.24)	(1.43)	**(2.41)**	(1.44)	–
	[1.06]	[1.03]	[1.03]	[1.08]	[1.00]
OTM	30.80	30.10	29.90	38.10	29.64
	(1.74)	(0.67)	(0.72)	**(5.18)**	–
	[1.04]	[1.02]	[1.01]	[1.29]	[1.00]
Puts					
All	34.48	33.53	33.80	27.52	32.14
	(5.67)	**(3.04)**	**(6.30)**	**(−3.16)**	–
	[1.07]	[1.04]	[1.05]	[0.86]	[1.00]
ATM	17.90	17.39	17.37	16.58	16.82
	(3.71)	(1.77)	**(3.08)**	(−0.25)	–
	[1.06]	[1.03]	[1.03]	[0.99]	[1.00]
OTM	43.01	41.82	42.24	32.68	39.98
	(6.06)	**(3.39)**	**(7.21)**	**(−4.15)**	–
	[1.08]	[1.05]	[1.06]	[0.82]	[1.00]

appears that deviations from fundamental volatility exhibit long-memory-like properties.

Second, comparing the asymmetric MacroGARCH(C) with the NGARCH(C) supports the conclusions of the single-component analysis. During the estimation period, accounting for business conditions improves the option-valuation performance of the component model by 6% on average. During the Great Recession, the improvement increases to 18%. Improvements are statistically and economically significant for all subsamples. Figure 4 clearly illustrates that, accounting for changes in business conditions, the MacroGARCH model outperforms the NGARCH(C) when the business conditions deteriorate.

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TABLE 8

Option-Pricing Results: Alternative Specifications
(Out of Sample, Dec. 2007–Oct. 2010)

The models considered in Table 8 all nest the NGARCH(C) model. Similar to Table 5, Table 8 reports, in percentage points, the average root mean squared error (%RMSE) for various subsamples of options between Dec. 2007 and Oct. 2010 (out of sample). For each subsample, I also report t-statistics (in parentheses) on the average of $\%\text{RMSE}_w^{\mathcal{M}} - \%\text{RMSE}_w^{\text{AMGC}}$ to assess whether model $\mathcal{M}$ is significantly outperformed by the asymmetric MacroGARCH(C) model ($_{\text{AMG}}$(c)); negative t-statistics arise when $\mathcal{M}$ dominates. The t-statistics are computed using Newey–West (1994) standard errors with a lag of 12 weeks and are bold whenever their magnitude is larger than 1.96. Additionally, I report the ratio (in square brackets) of the model's pricing error to that of the Aruoba–Diebold–Scotti (2009) (ADS)-based asymmetric MacroGARCH(C) model. GARCH stands for generalized autoregressive conditional heteroskedasticity, NGARCH stands for nonaffine GARCH, OTM stands for out of the money, and ATM stands for at the money. The corresponding implied-volatility root mean squared error results are reported in Table IA.2 in the Internet Appendix.

	%RMSE				
			MacroGARCH(C)		
	NGARCH(C)	NGARCH(C_3)	Rec. Prob.	VIX	Asym. ADS
All options	42.74	40.60	37.11	53.69	36.19
	(4.13)	**(4.07)**	(1.66)	**(3.73)**	–
	[1.18]	[1.12]	[1.03]	[1.48]	[1.00]
Maturity					
Short term	29.70	28.01	28.90	37.82	28.76
	(1.02)	(−0.90)	(0.42)	**(3.97)**	–
	[1.03]	[0.97]	[1.00]	[1.32]	[1.00]
Medium term	32.25	30.41	29.80	42.60	29.57
	(2.59)	(1.05)	(0.67)	**(3.90)**	–
	[1.09]	[1.03]	[1.01]	[1.44]	[1.00]
Long term	38.75	36.94	33.20	48.93	32.28
	(4.11)	**(4.30)**	(1.64)	**(3.63)**	–
	[1.20]	[1.14]	[1.03]	[1.52]	[1.00]
Calls					
All	33.38	30.88	28.97	48.63	28.72
	(2.03)	(1.14)	(0.37)	**(5.47)**	–
	[1.16]	[1.08]	[1.01]	[1.69]	[1.00]
ATM	21.41	19.88	17.45	30.24	17.12
	(4.01)	**(3.55)**	(0.86)	**(4.94)**	–
	[1.25]	[1.16]	[1.02]	[1.77]	[1.00]
OTM	39.03	35.91	34.19	58.74	33.79
	(1.70)	(0.85)	(0.50)	**(6.23)**	–
	[1.16]	[1.06]	[1.01]	[1.74]	[1.00]
Puts					
All	46.84	44.87	39.91	56.53	38.40
	(5.68)	**(6.48)**	**(2.78)**	**(3.06)**	–
	[1.22]	[1.17]	[1.04]	[1.47]	[1.00]
ATM	21.83	20.45	17.79	29.91	17.32
	(5.10)	**(5.04)**	(1.33)	**(3.98)**	–
	[1.26]	[1.18]	[1.03]	[1.73]	[1.00]
OTM	56.38	54.23	48.31	66.13	46.45
	(5.80)	**(6.54)**	**(2.96)**	**(2.91)**	–
	[1.21]	[1.17]	[1.04]	[1.42]	[1.00]

Finally, whereas NGARCH(C_3) performs better than the NGARCH(C) model, it is significantly outperformed by the asymmetric MacroGARCH(C) across most maturities and moneyness subsamples. During the Great Recession, the average improvement is 12%. Moreover, comparing Figure 5 with Figure 4, it is clear that i) the NGARCH(C_3) improvements over the NGARCH(C) are much more modest than those of the asymmetric MacroGARCH(C), and ii) the distribution of NGARCH(C_3) improvements is little related to business conditions.

B. An Alternative Macroeconomic Variable

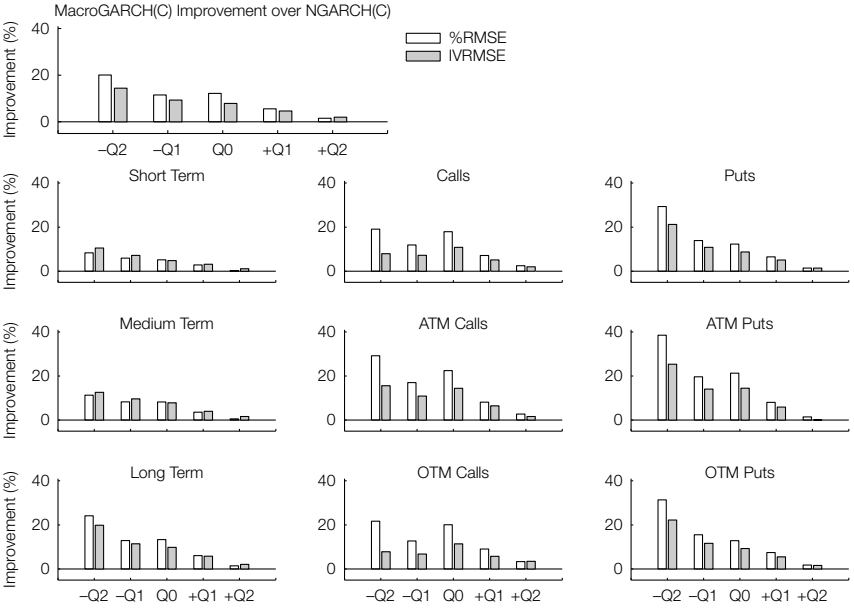
Among the many candidate macroeconomic variables available, I chose the ADS business conditions index. This index has the advantage of summarizing the

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FIGURE 4

Impact of Accounting for Changes in Business Conditions in a Component Model

Figure 4 reports the average relative pricing improvements obtained using the 2-component MacroGARCH(C) model instead of the 2-component nonaffine generalized autoregressive conditional heteroskedasticity (NGARCH(C)) model. The data are divided into five buckets corresponding to the quintiles of the Aruoba–Diebold–Scotti (2009) (ADS) business conditions index (x_t). In −Q2, business conditions are at their worst, whereas in +Q2, they are at their best. For each quintile, I average root mean squared error (RMSE) ratios (cf. Tables 7 and 8) obtained on each week in the quintile, and I report the average ratio (minus 1) of the NGARCH(C) model. Subsamples are obtained along the same lines as in Figure 2. IVRMSE stands for implied-volatility root mean squared error, and ATM stands for at the money.



informational content of six widely followed macroeconomic series. Moreover, it is updated whenever one of its constituents is, and it provides daily estimates of business conditions.

However, the methodology suggested in this article can accommodate any other series of interest. In particular, thanks to the MIDAS approach used to model the fundamental volatility process, series sampled at lower frequencies can be handled straightforwardly. Consider, for instance, the St. Louis Fed's Smoothed Recession Probabilities. These probabilities, updated monthly, are based on the work of Chauvet and Piger (2008) and are obtained from a dynamic-factor Markov-switching model applied to four monthly coincident variables: nonfarm payroll employment, index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales.

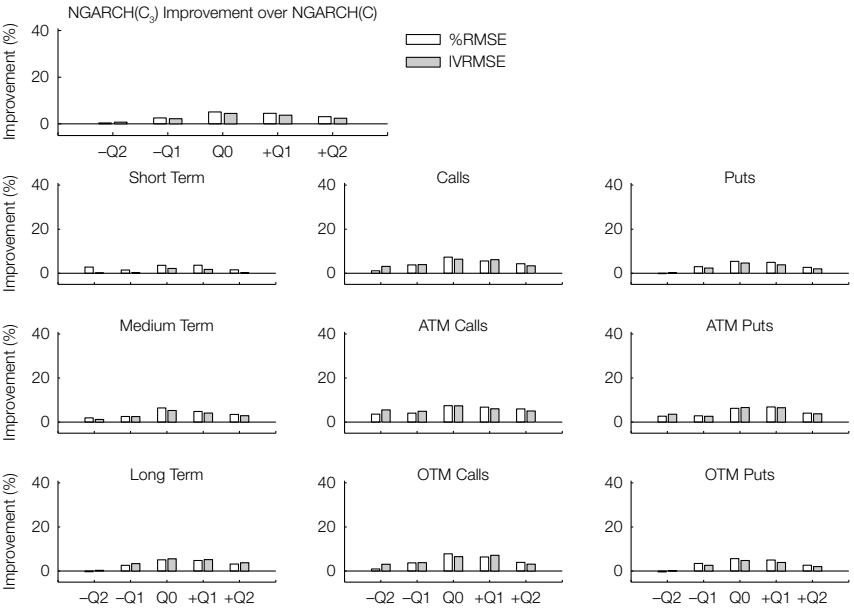
Tables 7 and 8 report the results obtained using these recession probabilities (RPs) instead of the ADS business conditions index in the estimation of the MacroGARCH model. The RP-driven model significantly outperforms the NGARCH(C) model on virtually all subsamples of options, both in the estimation period and out of sample. In the estimation period, the pricing errors of

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FIGURE 5

Impact of Adding a Third Autoregressive Component to the Component Model

Figure 5 reports the average relative pricing improvements obtained using the 3-component nonaffine generalized autoregressive conditional heteroskedasticity (NGARCH(C_3)) model instead of the 2-component NGARCH(C) model. The data are divided into five buckets corresponding to the quintiles of the Aruoba–Diebold–Scotti (2009) (ADS) business conditions index (x_t). In −Q2, business conditions are at their worst, whereas in +Q2, they are at their best. For each quintile, I average ratios of the NGARCH(C) root mean squared error (RMSE) to that of the NGARCH(C_3) (cf. Tables 7 and 8) obtained on each week in the quintile, and I report the average ratio (minus 1). Subsamples are obtained along the same lines as in Figure 2. IVRMSE stands for implied-volatility root mean squared error, and ATM stands for at the money.



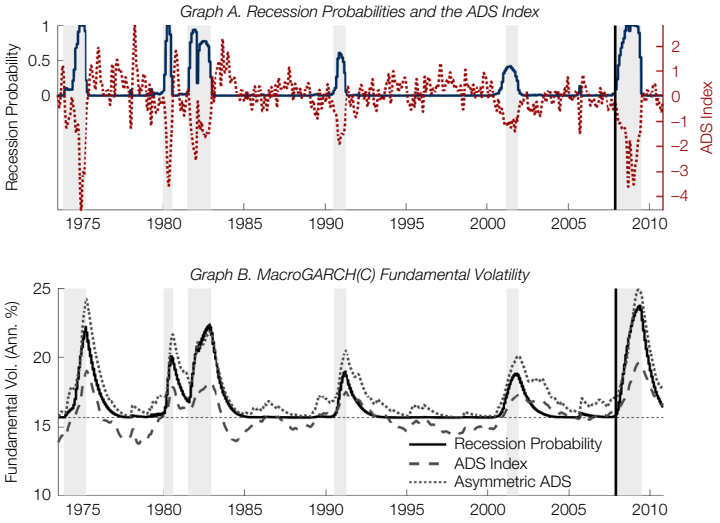
the RP-driven model are, on average, 2% (1.06 − 1.04) lower than those of the NGARCH(C). During the 2007–2009 Great Recession, this figure rises to 16%, the improvements ranging between 3% and 23%, with the biggest improvements being for long-term options.

These results confirm that my results are robust to the choice of macroeconomic variable. It is worth noting, however, that the asymmetric ADS-driven MacroGARCH significantly outperforms its RP-driven counterpart on most samples of options during the estimation period and in some out-of-sample periods. As illustrated by Figure 6, the RP-driven fundamental volatility loads positively on the probability of a recession. As such, the fundamental volatility of the RP-driven model is asymmetric in nature; higher RPs increase the fundamental volatility relative to the long-term average of the NGARCH(C), but because probabilities are never negative, lower probabilities do not lead to relatively low conditional volatility expectations. The main difference between the two models' fundamental volatility appears to be related to the timeliness of the underlying signal. In particular, before the 1990–1991 and the 2007–2009 recessions, the ADS index reflects the deterioration of business conditions before the recessions begin, while the RP is still very low.

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FIGURE 6
Recession Probabilities and Fundamental Volatility

Graph A of Figure 6 plots the St. Louis Fed's smoothed recession probabilities (solid line, left-hand-side axis) along with the Aruoba–Diebold–Scotti (2009) (ADS) business conditions index (dotted line, right-hand side) over the estimation period and out of sample starting Dec. 1, 2007 (black vertical line). Graph B plots the annualized fundamental volatility level of the MacroGARCH model driven by recession probabilities (solid line) and those of the MacroGARCH(C) driven by the ADS index (dashed line) and its asymmetric counterpart (dotted line). Gray-shaded regions highlight recessions dated by the National Bureau of Economic Research.



C. On the Singular Case of the VIX

Another macro-finance variable that is of particular interest in the context of my study is the CBOE VIX. Obviously, the VIX is a delicate special case in the context of my analysis. Indeed, the VIX level is extracted from the very options that I consider in my empirical applications. Hence, even with a 1-day lag, the VIX contains extremely rich information about the current option prices. Intuitively, one could expect that a well-specified option-valuation model based on the VIX should outperform most models. Moreover, any economic conclusion based on the performance of such a model must be drawn with care: Option prices are both the input and the target of a VIX-based model.

Besides, in my framework, the simplest VIX-based model specification leads to identification issues. Indeed, acknowledging that the VIX will typically be of the same order of magnitude as the model's annualized volatility, I can rewrite equation (30) as

$$\tau_{t+1} = \omega + \theta \sum_{k=0}^{K-1} \phi_k(w) x_{t-k} \quad \text{with} \quad x_t = \frac{1}{252}\text{VIX}_t^2. \tag{32}$$

Under these settings, maximum likelihood estimation yields a likelihood that is significantly better than that of any other model considered in this study.[19]

[19]The maximum likelihood estimates are not reported for space considerations but are available from the author.

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However, the persistence estimates are uncommonly low at $\beta_1 = 0.565$ and $\beta_2 = 0.945$. These low persistence estimates likely arise because the VIX is highly informative about short-run volatility, and thus, the identification of the fundamental volatility is poor. In particular, the correlation between the VIX-based model's high-frequency and fundamental volatilities, $\text{Corr}(h_t, \tau_t)$, is 93.7%. For the model based on the ADS business conditions index, this correlation is 7.8%.

Tables 7 and 8 report the results obtained using the VIX-based Macro-GARCH(C) model. During the estimation period, the VIX-based model significantly outperforms its ADS-based counterpart. Out of sample, however, the aforementioned identification issue leads to poor option-valuation performance for the VIX-based model. Regression results (untabulated) show that the VIX-based models performance significantly deteriorates when the VIX increases. Given its low persistence, during the Great Recession, the VIX-based model's volatility mean reverts much too fast to low levels.

V. Conclusion

I propose an option-valuation model, the MacroGARCH model, in which I depart from a paradigm that has been prevalent since Black and Scholes (1973) and consider the possibility that option values are partly determined by observable economic variables.

Empirically, I study an application to business conditions. Accounting for business conditions significantly improves the asset-pricing properties of the model on a 21-year panel of option prices observed between 1990 and 2010. In particular, my data set spans three recessions, and the MacroGARCH model's pricing errors during these recessions are between 15% to 42% lower than the errors obtained using a model that disregards business conditions.

These results hold during the 2007–2009 Great Recession, which is treated fully out of sample. Over a period that includes the latest financial crisis and its aftermath, the MacroGARCH model is 10% to 32% more accurate than its benchmark. Comparing component versions of the MacroGARCH model and its benchmark, the MacroGARCH model is still 18% more accurate, on average, than its 2-component benchmark out of sample.

This work offers several avenues for further research. Conrad and Loch (2015) find that expectations data from the Survey of Professional Forecasters improve volatility forecasts, and Buraschi, Trojani, and Vedolin (2014) suggest that dispersion in analyst forecasts is strongly related to implied volatility levels. Hence, incorporating analyst forecasts or survey results into the business conditions forecasting model could further improve the ability of the MacroGARCH model to explain observed option prices. Reciprocally, to the extent that expected changes in business conditions are reflected in option prices, option data might eventually be used to infer the market expectations of future business conditions. Besides, conducting a similar analysis in a stochastic volatility framework would allow researchers to assess the extent of the relation between the macroeconomic shocks entering the fundamental volatility process and the unobservable volatility shocks inherent in stochastic volatility models. Finally, a study of how the pricing kernel and higher moments of the stock returns' distribution evolve with changing

business conditions might further our understanding of the volatility premium and its time-series properties.

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