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Volatility Markets Underreacted to the Early Stages of the COVID-19 Pandemic

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VIX futures prices rose slowly in late February and early March 2020 as the COVID-19 pandemic took hold. Futures price premiums, defined as futures prices minus real-time statistical forecasts of future VIX values, turned sharply negative and remained negative until mid-April. Trading strategies based on estimated premiums profited from the subsequent increase in market volatility and equity market crash. The underreaction of futures prices to growing pandemic risks poses a puzzle for standard asset pricing models. (*JEL* G11, G13, G40)

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This article provides evidence that the VIX futures market underreacted to the growing risks of the COVID-19 pandemic during the pandemic's early stages. A simple example illustrates.

On March 2, 2020, the VIX stood at 33, up from 17 just over a week ago. By this date, coronavirus cases were spiking in Europe, and the United States had reported possible community spread as well as its first coronavirus-related death. The S&P 500 had fallen to just under 3100 from February highs.

With the VIX at 33, the VIX futures contract expiring March 18 settled at a futures price of 26, suggesting that the market expected the VIX to fall. The VIX tends to move predictably back toward its long-term average, which is around 20; in recent years, the average VIX has been even lower. Absent any other information, a futures price of 26 seems reasonable.

But precisely because the VIX predictably moves back toward its long-term average, one can also ask: On March 2, what would a statistical model have forecasted for the VIX on March 18? The answer, as I will discuss below, was higher—a value just exceeding 30.

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A futures price below the fair statistical forecast suggests an anomaly for standard equilibrium asset pricing models. VIX futures prices should exceed fair statistical forecasts because long futures investors should pay a premium over the forecast to hedge possible increases in uncertainty and market downturns. Therefore, futures price premiums, defined as futures prices minus forecasts, should be positive. They typically are and were as recently as February 21. But by March 2, premiums had fallen and were negative.

VIX futures prices fell further below statistical forecasts in early March as financial market volatility increased and news about the pandemic grew worse over time. On March 12, a day after the WHO declared the coronavirus outbreak a pandemic, the VIX jumped 21 points from 54 to 75. With just days until contract expiration, the March futures price gained only 12 points to settle at 58. This price was 7 points below that day's statistical forecast of 65 for the VIX, a sizeable deficit not seen since the 2008 financial crisis. The VIX increased to 83 a few days later and remained above 70 for several days afterward; the March futures ultimately settled at 70.

Overall, futures prices rose slowly compared to statistically fair forecasts of the VIX as pandemic risks grew, leading premiums to fall. I refer to falling premiums as "underreaction" since standard asset pricing models predict that premiums rise when risk rises. In March, the underreaction was so large that premiums sank to negative levels. Of course, both futures prices and statistical forecasts were lower than the VIX on the March futures expiration date after the fact. But real-time ex ante estimates of negative premiums tended to precede ex post futures price increases, and strategies that used these estimates as signals to time long futures positions earned large profits. These facts suggest the estimates contain valid information.

Moving into April and May, premiums climbed back to positive levels, with futures prices exceeding fair statistical forecasts of the VIX. Concurrently, growth rates in U.S. COVID-19 cases fell, and financial market risk declined. Ex ante higher estimates of premiums tended to precede ex post futures price decreases. Strategies using estimated premiums as signals exited long futures positions and retained a large portion of the profits earned earlier in March.

The first half of this article fleshes out this preceding narrative; the second half shows that the underreaction of VIX futures prices to growing pandemic risks was a vivid example of systematic underreaction to risks that occur over the history of the VIX futures market. Examining whether underreaction systematically occurs helps address the worry that the preceding narrative was just a fluke of estimated premiums or unreliable due to the pandemic's short sample. Indeed, definitive statistical conclusions based solely on the pandemic are challenging to draw due to the short sample of just a few months.

Several findings together support this conclusion of systematic underreaction. First, estimated futures price premiums, or "VIX premiums" (Cheng

2019), provide a genuine signal of true premiums because they predict movements in futures prices with the expected magnitude. Second, a trading strategy that times VIX premiums produces large risk-adjusted returns net of transaction costs. Third, increases in ex ante risk tend to push premiums lower before reversing later, and lower premiums forecast higher ex post risk than usual. These relationships were observable to the market by the end of 2019, and these results update the results of Cheng (2019), whose sample ends in 2015.

Even considering these systematic patterns, the COVID-19 pandemic vividly exemplifies underreaction to risk. The only comparable episode of underreaction is the 2008 financial crisis. The H1N1 pandemic and Ebola epidemic were comparatively minor episodes, likely because these events were minor shocks for financial markets. The H1N1 pandemic barely moved estimates of VIX premiums, which stayed positive for nearly the entire duration of the episode. Premiums briefly fell into negative territory during the Ebola epidemic, but the absolute magnitude was small.

The underreaction poses a puzzle for standard asset pricing models and points to the need for more research to explain its sources and how markets respond to pandemics. Existing research on volatility derivatives and variance risk premiums (for a review, see Carr and Lee 2009; for early work, see Coval and Shumway 2001 and Bakshi and Kapadia 2003) do not include a role for negative premiums in equilibrium models (e.g., Bollerslev, Tauchen, and Zhou 2009; Drechsler and Yaron 2011; Eraker and Wu 2017).

One important question is whether underreaction occurs due to mispricing or rational pricing under alternative models; the results here do not distinguish between the two. On the one hand, premiums could fall and rationally become negative if increases in volatility correspond to low marginal utility states, possibly due to heightened expectations of government stimulus or bailouts.[1] All else equal, a rational pricing story may be important since academic research reduces mispricing (McLean and Pontiff 2016) and because the COVID-19 pandemic is an out-of-sample exemplar of the previously published “low premium-response puzzle” in Cheng (2019).

On the other hand, the results are consistent with the behavioral explanation proposed by Lochstoer and Muir (2019). In their model, premiums underreact to risk in equilibrium because the representative agent has biased, slow-moving expectations about volatility. More broadly, the limits of arbitrage make it especially difficult for rational arbitrageurs to trade negative premiums. One potentially important clue is the substantial heterogeneity in how dealers, asset managers, and hedge funds approached the COVID-19

[1] I thank a referee for this insight. Kelly, Lustig, and Van Nieuwerburgh (2016) show that government guarantees increased the spread between put options on individual banks and the financial sector during the 2008 financial crisis.

pandemic in their VIX futures trading. Heterogeneous trading motives may be important for understanding time-varying premiums.

1. The Early Stages of the COVID-19 Pandemic

1.1 February and early March 2020

Table 1 lists the values of the S&P 500, VIX, VIX futures settlement prices, and fair statistical forecasts for each futures expiration date through time. Panel A starts in mid-February and runs through mid-March, the initial period when the pandemic was just starting to unfold. Data starting in March 2004 running through May 2020 come from Bloomberg Professional.

On February 19, the S&P 500 closed at a record high, just 14 points shy of 3400. The VIX closed around 14, a value which was, as with most days over the bull market of the preceding years, well below its historical average of 20. These events occurred even though the first U.S. case associated with the novel coronavirus had been reported in the mainstream news and confirmed by the CDC on January 21. The news out of China had been dire up until that point; on February 12, the media reported 14,000 new cases in Hubei Province alone. By March 2, the news was getting worse: cases were spiking in Europe, and the United States had reported possible community spread as well as its first coronavirus-related death. The S&P 500 had fallen to just under 3100. The VIX had risen to 33, a substantial increase from 14.

The news worsened from there: after March 2, Italy placed travel restrictions on the northern part of the country, the United States restricted travel from Europe, and the WHO officially declared the outbreak a pandemic. Some states, including California, New Jersey, and Maryland, began declaring states of emergency. The Federal Reserve announced a 50-basis-point rate cut on March 3, and Congress passed legislation to respond to the virus on March 6. But on March 9, the market plunged 7% at the open, precipitating a trading halt on the NYSE, and by March 12, the VIX had exploded to 75. By the end of that week, the United States declared a national emergency.

These events set the stage for March 16, one of the worst days in financial markets since the 2008–2009 financial crisis. On the Sunday going into the week, the Federal Reserve announced a 100-basis-point cut to the target federal funds rate, asset purchases, and action to strengthen dollar liquidity. However, on Monday morning, the market panicked. Money market funds faced massive redemptions as investors fled for hard cash, and liquidity evaporated in credit markets. By the end of the day, the S&P 500 had fallen 12%, and the VIX had reached a record 83.

1.2 VIX futures prices rose slowly compared to statistical forecasts

As suggested in the introduction, futures prices were effectively too slow to rise in this early stage of the outbreak compared to fair statistical forecasts of where the VIX would be on futures expiration dates. For example, with the

Table 1
SPX, VIX, VIX futures, and VIX forecasts

A. February and March 2020

			March 18 futures			April 15 futures			
Date	SPX	VIX	Price	Fcast.	VIXP	Price	Fcast.	VIXP	Notes
Feb 12 (Wed)	3,379.45	13.74	15.32	15.26	0.06	16.13	15.80	0.33	14,000 new cases in Hubei, China
Feb 13 (Thu)	3,373.94	14.15	15.57	15.33	0.24	16.33	15.86	0.47	
Feb 14 (Fri)	3,380.16	13.68	15.43	14.99	0.44	16.13	15.56	0.56	First deaths in Europe
Feb 18 (Tue)	3,370.29	14.83	15.82	15.48	0.35	16.52	15.98	0.54	
Feb 19 (Wed)	3,386.15	14.38	15.38	15.22	0.16	16.33	15.76	0.56	S&P 500 record high
Feb 20 (Thu)	3,373.23	15.56	16.08	15.80	0.27	16.83	16.26	0.57	27 countries; 75,000 cases; 2,100 deaths
Feb 21 (Fri)	3,337.75	17.08	16.92	16.65	0.27	17.33	16.99	0.33	Cases in Iran and South Korea surge; 34 U.S. cases
Feb 24 (Mon)	3,225.89	25.03	20.08	21.11	−1.03	19.38	20.82	−1.44	Cases in Italy surge
Feb 25 (Tue)	3,128.21	27.85	22.23	23.31	−1.09	20.88	22.72	−1.84	CDC issues warning for U.S.; outbreak spreads in Europe
Feb 26 (Wed)	3,116.39	27.56	22.33	23.91	−1.59	20.98	23.23	−2.26	First possible U.S. community spread; Germany warns of impending epidemic
Feb 27 (Thu)	2,978.76	39.16	26.27	31.00	−4.72	23.52	29.30	−5.77	European cases surge
Feb 28 (Fri)	2,954.22	40.11	26.33	32.95	−6.63	23.02	30.97	−7.94	56 countries; 84,000 cases; 2,900 deaths
Mar 2 (Mon)	3,090.23	33.42	26.27	30.28	−4.01	23.33	28.69	−5.36	First U.S. deaths over the prior weekend; several states declare emergencies
Mar 3 (Tue)	3,003.37	36.82	29.17	32.71	−3.53	25.52	30.75	−5.22	*Federal Reserve 50-bp emergency cut*
Mar 4 (Wed)	3,130.12	31.99	27.42	30.55	−3.12	24.63	28.92	−4.29	California declares state of emergency
Mar 5 (Thu)	3,023.94	39.62	31.88	35.19	−3.32	27.52	32.83	−5.31	New Jersey and Maryland declare states of emergency
Mar 6 (Fri)	2,972.37	41.94	35.78	37.50	−1.72	30.33	34.77	−4.45	90 countries, 100,000 cases, 3,400 deaths; Coronavirus Preparedness and Response Act becomes U.S. law
Mar 9 (Mon)	2,746.56	54.46	44.38	46.21	−1.84	36.22	42.02	−5.80	National lockdown in Italy; U.S. markets level 1 trading halt
Mar 10 (Tue)	2,882.23	47.30	41.83	43.54	−1.72	34.78	39.92	−5.14	23 U.S. states with states of emergency
Mar 11 (Wed)	2,741.38	53.90	46.35	48.69	−2.34	38.58	44.03	−5.45	WHO declares pandemic
Mar 12 (Thu)	2,480.64	75.47	58.30	65.19	−6.89	45.83	57.05	−11.2	Worst day for U.S. stock market since 1987; level 1 trading halt
Mar 13 (Fri)	2,711.02	57.83	53.42	55.75	−2.32	43.90	50.50	−6.60	U.S. declares a national emergency; 121 countries; 143,000 cases worldwide

B. March and April 2020

Date	SPX	VIX	April 15 futures			May 20 futures			Notes
			Price	Fcast.	VIXP	Price	Fcast.	VIXP	
Mar 16 (Mon)	2,386.13	82.69	59.15	64.68	−5.53	44.88	56.34	−11.5	States close schools; first death in NY; Level 1 trading halt *Federal Reserve 100-bp cut; announcement of asset purchases; lower reserve requirement; lower rate on central bank swap lines*
Mar 17 (Tue)	2,529.19	75.91	61.42	64.89	−3.46	48.70	57.12	−8.42	EU closes borders; President Trump invokes DPA; *Fed announces PDCF, CPFF*
Mar 18 (Wed)	2,398.10	76.45	70.47	65.97	4.50	59.92	57.95	1.98	Families First Coronavirus Response Act becomes U.S. law; *Fed announces MMLF*; level 1 trading halt
Mar 19 (Thu)	2,409.39	72.00	66.30	64.36	1.94	58.97	56.68	2.29	13,000 U.S. cases; stay-at-home order in California; *Fed establishes swap lines with more int'l central banks*
Mar 20 (Fri)	2,304.92	66.04	61.53	60.90	0.63	56.63	53.73	2.89	18,000 U.S. cases; U.S. tax deadline moved to July 15; *MMLF collateral expansion*
Mar 23 (Mon)	2,237.40	61.59	49.45	57.85	−8.40	45.33	51.05	−5.72	United Kingdom enters lockdown; 330,000 cases worldwide *Fed announces PMCCF, SMCCF, TALF, and expanded asset purchases*
Mar 24 (Tue)	2,447.33	61.67	48.25	57.49	−9.24	40.15	50.61	−10.5	50,000 U.S. cases; Olympics postponed; India enters lockdown
Mar 25 (Wed)	2,475.56	63.95	51.28	58.96	−7.68	44.53	51.80	−7.28	WHO warning of medical supply shortage; deal reached on CARES Act in United States
Mar 26 (Thu)	2,630.07	61.00	45.88	57.59	−11.7	39.65	50.79	−11.1	3.3 M unemployment claims; United States leads in no. of cases; NYC becomes epicenter; *NY Fed to buy commercial mortgages*
Mar 27 (Fri)	2,541.47	65.54	53.42	60.33	−6.90	44.83	52.90	−8.07	CARES Act becomes U.S. law; U.K. PM Boris Johnson tests positive
Mar 30 (Mon)	2,626.65	57.08	49.78	55.73	−5.95	42.75	49.40	−6.65	30,000 global deaths; United States extends stay-at-home guidelines

Mar 31 (Tue)	2,584.59	53.54	46.78	52.82	−6.04	40.92	46.67	−5.74	*Fed announces Foreign and Int'l Monetary Authority Repo Facility*
Apr 01 (Wed)	2,470.50	57.06	51.33	54.60	−3.27	44.63	47.87	−3.25	Italy lockdown extension; *Fed loosens leverage ratio requirements*
Apr 02 (Thu)	2,526.90	50.91	47.17	50.90	−3.72	42.03	45.09	−3.06	6.6 M U.S. unemployment claims (later revised to 6.8 M) 1 M cases; 50,000 deaths worldwide
Apr 03 (Fri)	2,488.65	46.80	44.92	47.55	−2.62	40.90	42.20	−1.30	SBA announces PPP loans
Apr 06 (Mon)	2,663.68	45.24	41.78	45.82	−4.04	37.92	40.65	−2.72	*Fed preannounces PPPLF*
Apr 07 (Tue)	2,659.41	46.7	44.03	46.39	−2.37	39.67	40.97	−1.30	
Apr 08 (Wed)	2,749.98	43.35	42.38	43.95	−1.58	38.30	39.23	−0.93	1.5 M cases
Apr 09 (Thu)	2,789.82	41.67	41.28	42.23	−0.96	36.92	37.85	−0.93	(Another) 6.6 M U.S. unemployment claims; *PPPLF, MSLF, MuniLF, expanded PMCCF, SMCCF, and TALF announcement*
Apr 13 (Mon)	2,761.63	41.17	40.58	41.47	−0.89	36.13	37.23	−1.10	
Apr 14 (Tue)	2,846.06	37.76	37.88	38.37	−0.49	32.97	35.19	−2.22	NYC death toll passes 10,000
Apr 15 (Wed)	2,783.36	40.84	42.5[a]			36.58	36.38	0.19	SBA PPP loan funding exhausted
Apr 16 (Thu)	2,799.55	40.11				36.53	36.21	0.31	5.2 M unemployment claims White House releases guidelines to reopen

This table reports the values of the S&P 500, VIX, VIX futures daily settlement prices, and VIX forecasts. Notes come from the Think Global Health project (by the Council on Foreign Relations), Federal Reserve Board, St. Louis Fed FRASER website, and a search of *New York Times* and *Wall Street Journal* articles. Italics indicate a Fed action. [a]The futures final settlement value determined by a special opening quotation of the VIX.

VIX at 33 on March 2, the futures price for a contract expiring March 18 settled at 26, even though a statistical forecast would have placed the VIX higher at 30 for that expiration date. When the VIX closed at 75 on March 12, the March futures settled at 58 while statistical forecasts put the VIX at 65. When the VIX closed at 83 on March 16, the May futures settled at 45 while statistical forecasts put the VIX at 56.

To produce these statistical forecasts, I use daily data to estimate a standard statistical model that assumes the VIX follows an ARMA process. An ARMA process captures two key features. The autoregressive (AR) component captures mean reversion, or the tendency of the VIX to move toward its long-term average. The moving average (MA) component captures the possibility that recent unexpected VIX movements may directly affect short-term fluctuations. Cheng (2019) estimates an ARMA(2,2) model using daily data on the VIX from its starting date in 1990 through the start of 2004 and finds that it fits well compared to several other forecast models. I update the methodology in that paper by estimating the ARMA model using an expanding window that uses, for any given trading date, all available data of the VIX starting in 1990 up until the previous trading date. I then use estimates from the model combined with information up to the trading date to obtain statistical forecasts of the VIX as of each futures expiration date.

The estimated futures price premium, or "VIX premium," equals the futures price minus the statistical forecast:

$$VIXP_t = F_t^T - \widehat{VIX}_t^T, \tag{1}$$

where F_t^T is the date-t futures price for a contract on date expiring on date T and $\widehat{VIX}_t^T$ is the estimated model's forecast for the VIX for date T as of date t. The VIX premium equals the estimated expected premium a long investor pays on a VIX futures contract over the remaining life of the contract, before applying the contract multiplier. Equivalently, it equals the estimated expected profit for a short VIX futures position. Table 1, panel A, shows that, as the market became increasingly gripped by worsening news about the COVID-19 pandemic toward the end of February and early March, estimated VIX premiums fell and became negative.

Figure 1 illustrates that the 1-month VIX premium fell and became negative. The 1-month premium chains together premiums from different futures contracts into a single time series. On any given day, the premium references the contract expiring the next month; on the last day of the month, the premium "rolls" the reference contract forward. For example, the 1-month premium in February references the March contract; on the last day of February, the premium rolls and references the April contract until the end of March. On the last day of March, the premium rolls and references the May contract until the end of April, and so on.

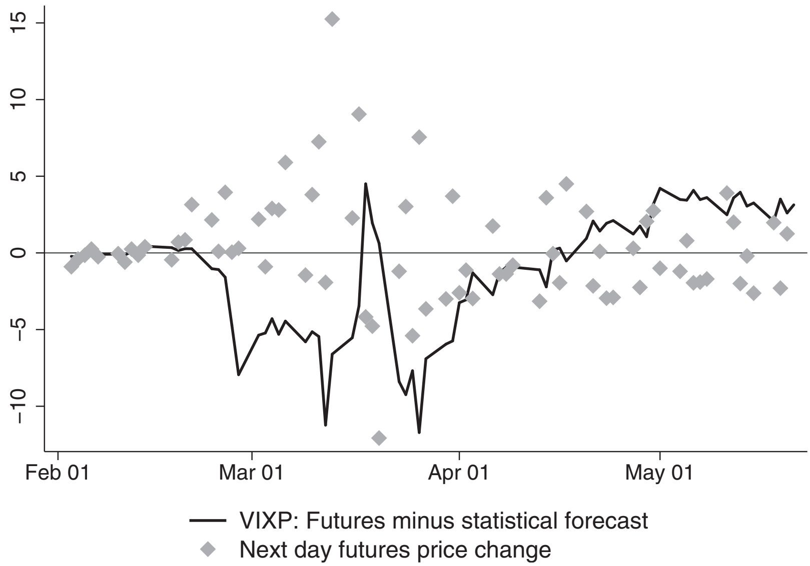

Figure 1
VIX premiums, February–May 2020
This figure plots the 1-month VIX premium given in Equation (1). The premium in month t references the contract expiring in month t+1. The dots represent the futures price change over the next day.

In late February and early March, VIX premiums sank to some of the largest negative values in the history of the market. Prices on March 2 implied a 1-month premium from the April contract of -5.4, while prices on March 12 implied a premium of -11.2. For comparison, Table 2 reports summary statistics for 1-month premiums over the history of the VIX futures market. The value of -5.4 is close to the first percentile, and the value of -11.2 is one of the lowest ever.

1.3 Premiums returned to positive levels by mid-April

Table 1, panel B, picks up the narrative again as volatility continued the week of March 16. Market turmoil led the Federal Reserve to roll out a battery of financial stability measures in a matter of days that had taken months to implement in the 2008 financial crisis. Congress passed, and President Trump signed, additional legislation to mitigate the economic and health consequences of the coronavirus. U.S. cases reached 18,000 by the end of the week, up from 2,000 the Friday before and 300 the Friday before that.

On March 18, premiums suddenly climbed back to positive levels but fell just as suddenly back to negative levels on March 23. The sudden increase occurred when the April futures price rose almost 9 points to 70.5 despite much only minor changes in the VIX and accompanying statistical forecasts. Amidst all the volatility, it briefly looked as if the underreaction had suddenly

Table 2
Summary statistics for VIX premiums

			Percentiles								
Month	Mean	SD	1st	5th	25th	50th	75th	95th	99th	Days < 0	T
1	0.68	1.91	−5.98	−1.30	−0.14	0.56	1.53	3.65	5.30	29%	4,067
2	1.30	2.69	−7.20	−1.60	0.01	1.02	2.59	5.64	7.01	25%	3,370
3	1.59	2.91	−7.27	−1.65	−0.05	1.14	3.05	6.33	8.27	26%	3,370
4	1.84	3.10	−6.70	−1.62	−0.09	1.23	3.58	7.02	9.10	27%	3,370
5	2.05	3.28	−6.53	−1.54	−0.11	1.22	4.05	7.85	9.82	27%	3,370

This table reports the summary statistics for *VIXP* (Equation (1)) through May 21, 2020, at the daily frequency. Values reference the *n*-month-ahead contract over the month. For example, the 1-month premium in February 2020 references the March 2020 contract; on the last day of February, the premium rolls and references the April contract until the end of March. On the last day of March, the premium rolls and references the May contract until the end of April. Units are expressed as VIX points. The 1-month data series starts in the year 2004, when VIX futures start trading, and references the next available contract if a 1-month contract is not available. The 2, 3, 4, and 5-month data series start in 2007, when a complete term structure is available every month.

unwound, and that premiums returned to positive levels. But premiums sank just as suddenly back to negative levels when the April futures price fell 12 points to 49.5 on March 23 despite only a 5-point fall in the VIX to 61.5.

From March 23 onward, the stock market rebounded despite the release of grim economic numbers. On March 26, the Department of Labor reported that initial unemployment claims over the prior week totaled 3.3 million, a number that dwarfed the previous high by a factor close to five. Nonetheless, this was better than market expectations as the S&P 500 rose 6% and the VIX fell. That week, the federal government also enacted the CARES Act to provide fiscal stimulus, and the Federal Reserve continued to implement measures to support financial stability.

During the rebound in early April, negative premiums increased and moved toward positive levels, as Table 1 and Figure 1 illustrate. The 1-month premium moved from a low of -11.7 on March 26 (referencing the April contract) to +0.31 by April 16 (referencing May). By that date, the S&P 500 was at 2,800 with the VIX at 40.

1.4 Estimated premiums contained information about true premiums

Negative premiums are an anomaly for standard asset pricing models. Premiums should be positive, with futures prices exceeding fair forecasts. The reason is that a long VIX futures investor should expect to pay a positive premium to hedge possible increases in uncertainty and market downturns (e.g., as in Bollerslev, Tauchen, and Zhou 2009; Drechsler and Yaron 2011; Eraker and Wu 2017). Negative premiums imply undervalued futures prices in the context of these models.

Empirically, Table 2 reports that the unconditional average VIX premium is positive over the history of VIX futures. By itself, this fact is consistent with these models. It is also sensible considering the negative market beta and positive realized volatility exposure of VIX futures; both these effects push premiums higher (Cheng 2019; Dew-Becker et al. 2017).

Table 2 also shows that estimated premiums fluctuate substantially and are negative on 25%–30% of days in the history of VIX futures. On the one hand, one would expect to observe *some* negative estimated premiums due to noise in the statistical estimation process if true premiums periodically fluctuated close to zero.[2] On the other hand, such noise would need to be conditionally large to explain large negative values of estimated VIX premiums, such as those observed in late February and early March.

To gauge whether estimated premiums contain information for true premiums, I check whether estimated premiums predict movements in futures prices.

Figure 1 shows that negative VIX premium estimates in February and March tended to anticipate daily increases in futures prices, consistent with true negative premiums. The chart plots the 1-month VIX premium in the solid line and the change in the futures prices over the next day for the 1-month reference contract in dots. Comparing the line to the dots suggests that the line (ex ante premiums) tends to be negative when the dots are positive (ex post changes in futures prices) and vice versa.

The short sample from February through May makes it challenging to draw reliable statistical conclusions about the relationship between ex ante premiums and highly volatile ex post futures price changes. However, for illustration purposes, I note that a simple regression of tomorrow's futures price change (the dots plotted in Figure 1) on today's premium (the solid line) yields an estimated slope of -0.28, an ordinary least square (OLS) standard error of 0.10, and an R^2 value of 9% over 76 trading days. The estimated intercept is -0.01 with an OLS standard error of 0.41. Together, these suggest that high premiums were followed by futures price decreases, and vice versa. One should interpret these estimates cautiously as they may be influenced by outliers over the short sample. Section 2 systematically examines the forecast power of premiums for ex post price changes.

I also check whether threshold trading strategies generate profits. A threshold strategy is long futures, short futures, or in cash based on the sign of the premium. For example, a "long/short" threshold strategy is a dynamic strategy that holds long 1-month futures over date t if $VIXP$ is less than zero on date $t-2$ and short futures if $VIXP$ is greater than zero, with any necessary buy, sell, or roll transactions occurring on date $t-1$. If $VIXP_{t-3} > 0$ but $VIXP_{t-2} < 0$, the strategy would hold a short position over date $t-1$ and then transact into a long position at the end of $t-1$ before holding that position over date t. The strategy rolls a short or long position forward at the end

[2] Direct estimates of 30-day variance risk premiums can also turn negative, particularly in advance of major market downturns (Bekaert and Hoerova 2014). Compared to VRPs, VIX premiums turn negative at a higher rate. One likely reason is that VIX premiums are forward claims slightly down the term structure of variance, which have a lower risk price (Cheng 2019; Dew-Becker et al. 2017).

of each month to the new 1-month contract. The strategy is monitored daily, and the trading signal dated $t-2$ is available in real-time on date $t-1$.

I assume that any transactions occur at bid and ask prices. The bid-ask spread is important because the strategy transacts at least once a month (during the roll) and because spreads can widen in times of major market movements. For simplicity, I abstract from issues relating to leverage and assume full collateralization with an absolute leverage of 1. Daily excess returns are thus percentage price changes (for long positions) or their negative (for short positions).

Figure 2 and Table 3 show that threshold strategies that go long when premiums were negative generated profits in the period starting February 1. Both the "long/cash" and "long/short" strategies generated cumulative excess returns exceeding 200% through March 27 owing to long positions in futures that had been opened when premiums were negative. Each strategy gave back some of those profits in early April when premiums were moving back to positive territory but were still negative. During this period, futures prices decreases became increasingly more common, causing these strategies to suffer some losses before exiting their long positions in mid-April. Both strategies, though, retained most of their profits. After mid-April, the "long/short" strategy began to catch up to the "long/cash" strategy. This suggests that exiting long positions, even though slightly late, was the right call in that long positions were no longer profitable.

Given that equity markets fell in March before rebounding, the analysis above suggests that strategies that went long futures when the premium was negative likely generated market risk-adjusted returns. Section 2 returns to this issue in the context of the broader historical evidence.

Strategies that went cash or short when premiums were negative performed poorly. The "cash/short" strategy missed out on most of the profits captured by long strategies during this period. The "short/short" strategy, which explicitly takes short positions even when premiums are negative, incurred large losses, with an average daily return of -1.6% per day during this period compared to positive average returns for all other strategies in Table 3.

1.5 Premiums fell as COVID-19 cases grew and financial market risk rose

The period of negative premiums in March corresponded to the period of the highest growth rate of COVID-19 cases and deaths in the United States. Figure 3 plots the VIX premium against the daily growth rate of confirmed U.S. cases and deaths over the preceding week. Data on cases and deaths comes from Johns Hopkins University.[3] Premiums were negative in March precisely when growth rates were high; premiums reversed into positive

[3] Available online at https://coronavirus.jhu.edu/map.html. Results using data from the *New York Times* COVID-19 database (https://github.com/nytimes/covid-19-data) yield identical conclusions. I take growth rates over 1 week to account for day-of-the-week effects in the growth rate.

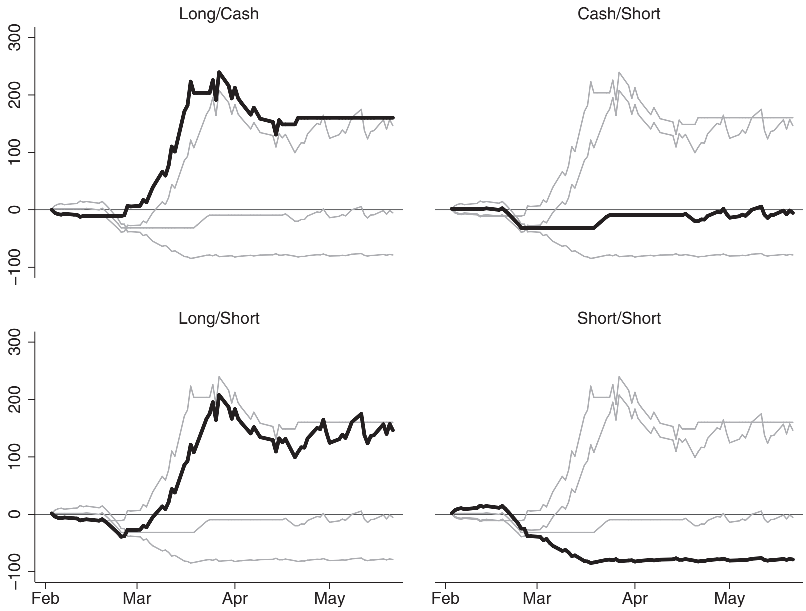

Figure 2
Trading profits
This figure plots the cumulative excess return of four threshold trading strategies starting on February 1, 2020, through the end of the sample. Units on the vertical axis are percentage points, and ticks on the horizontal axis represent the first of each month.

Table 3
Trading profits

	Mean	SD	Skew	Kurt.	Percentiles 5th	50th	95th	T
S&P 500	−0.05	3.55	−0.21	4.83	−5.19	0.02	6.24	77
Long/cash	1.48	7.12	2.02	8.66	−7.08	0.00	17.69	77
Long/short	1.54	8.76	0.82	4.72	−10.53	0.80	18.79	77
Long/long	1.39	8.79	0.98	4.63	−8.02	−0.86	18.61	77
Cash/short	0.06	5.12	−0.36	7.39	−9.34	0.00	7.43	77
Short/short	−1.57	8.81	−0.95	4.51	−18.61	0.61	8.02	77

This table reports summary statistics for excess returns for the S&P 500 and five threshold trading strategies starting on February 1, 2020. Units are expressed as daily (nonannualized) percentage points.

territory in April and May when growth rates were lower. Interestingly, the blip of positive premiums in mid-March corresponds with a brief dip in the growth rate in cases. The correlation of case growth rates and premiums is negative: -0.75 in levels and -0.12 in changes. The fact that premiums were negative when growth rates were high is puzzling because the period of high growth rates was plausibly when uncertainty about the pandemic going forward was the highest.

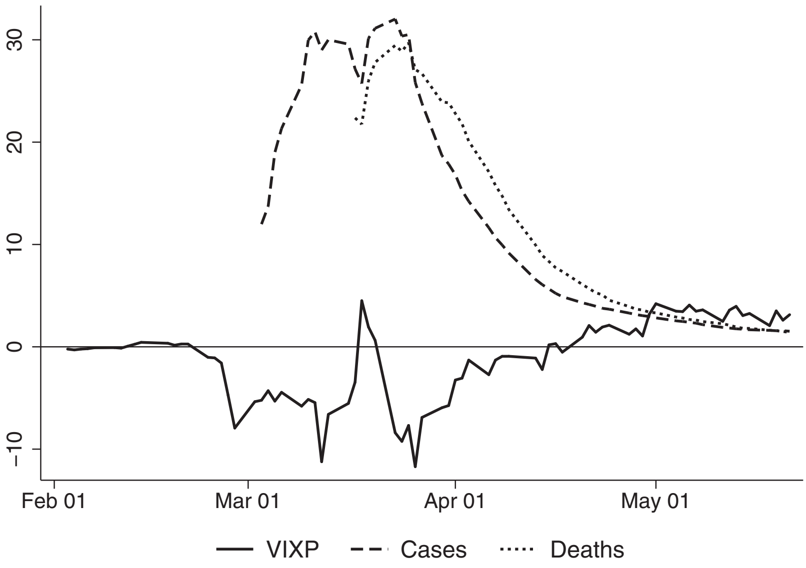

Figure 3
VIX premiums and U.S. COVID-19 cases and deaths
This figure plots the 1-month VIX premium along with the continuously compounded daily growth rate in confirmed U.S. COVID-19 cases and deaths each week. Growth rates for cases and deaths are plotted once the level of each exceeds 100 and are expressed as percentage points.

Consistent with this idea that premiums fell when uncertainty rose, premiums fell just when financial market risk going forward was increasing. Figure 4 plots the VIX premium alongside the VVIX and VIX indices. The VVIX (CBOE "VIX of VIX") index measures the forward-looking 30-day (risk-neutral) volatility of VIX futures price changes and is calculated from VIX option prices. If premiums increase with risk, one should see the VIX premium rise when the VVIX rises. But even though the VVIX eventually rises from late February to a high of 60% per month in mid-March (or over 200% annualized, a record value), premiums fell and became negative over this period. Premiums blipped into positive territory in mid-March—just when there was a slight dip in COVID-19 cases, according to Figure 3—but largely remained negative until the VVIX declined in April and May. In this later period, premiums rose when uncertainty fell. Similar patterns emerge when comparing premiums with the VIX itself.

Figure 5 plots the Chicago Fed National Financial Conditions Index (NFCI) alongside premiums to explore an alternative measure of financial market risk.[4] The weekly index summarizes information from financial indicators known to correlate with risk, credit market conditions, and leverage, including the TED spread, OIS-Treasury yield spread, ABS-Treasury yield

[4] Available online at https://www.chicagofed.org/publications/nfci/index.

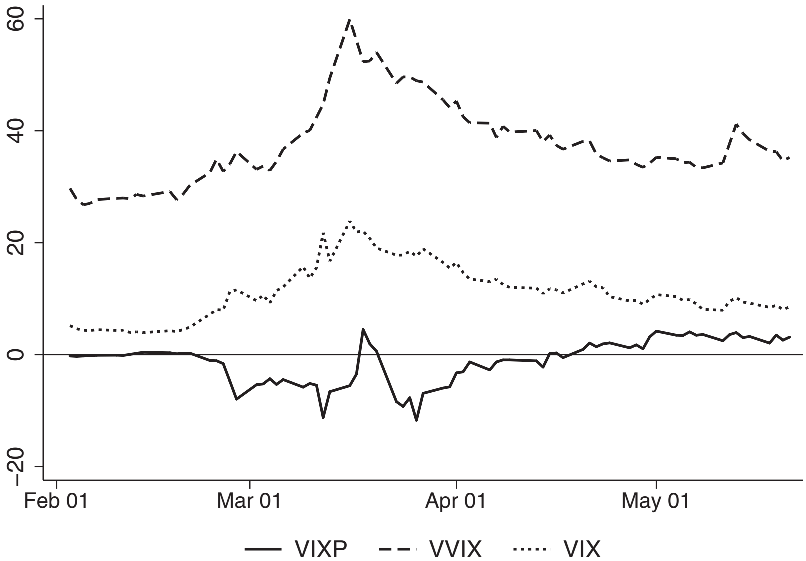

Figure 4
VIX premiums and financial market risk
This figure plots the 1-month VIX premium along with the VVIX and VIX converted to monthly percentage points.

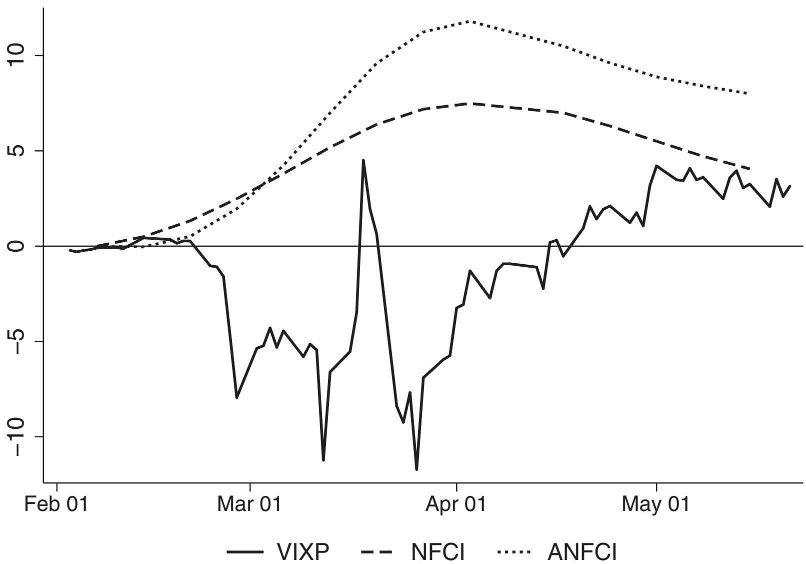

Figure 5
VIX premiums and financial market conditions
This figure plots the 1-month VIX premium along with the weekly Chicago Fed National Financial Conditions Index (NFCI) and Adjusted National Financial Conditions Index (ANFCI), normalized to zero in January 2020 and scaled by a factor of 10. Higher values indicate tighter financial conditions.

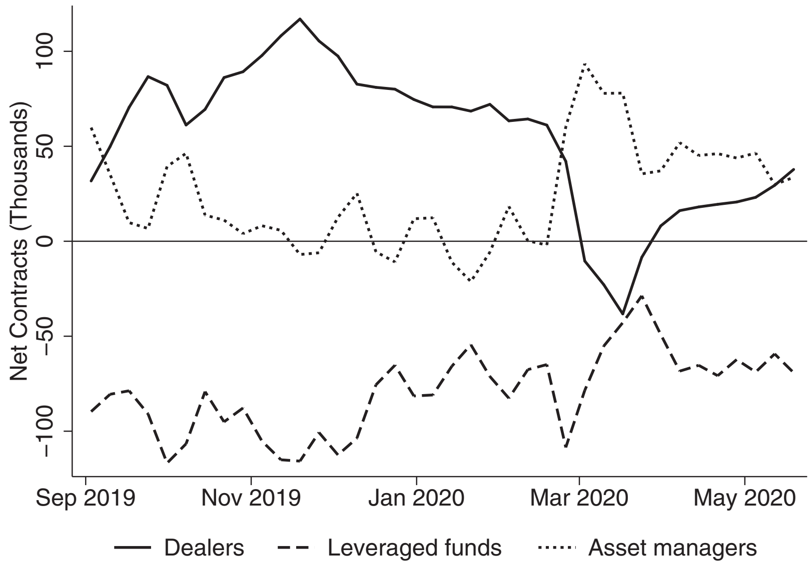

Figure 6
Trader positions
This figure plots weekly net positions (long minus short) of aggregate trader groups in VIX futures. Net short positions are plotted as negative values, and net long positions are plotted as positive values. The figure omits "Other reportable traders" and "Nonreportable traders."

spread, Treasury repo delivery fail rate, CDS indices, corporate bond yield spreads, and many more. The adjusted NFCI isolates the component of financial conditions uncorrelated with economic conditions. The figure shows that financial conditions were worsening throughout March as VIX premiums fell into negative territory before financial conditions eased in April.

Who was selling and buying during this period? The data indicates that dealers reduced their net long positions in late February and March before rebuilding those positions in April and May. Asset managers went from neutral to long, while leveraged hedge funds reduced their short positions. Figure 6 plots the net trader position of aggregate trader groups in VIX futures through time. The data come from the Commodities Futures Trading Commission (CFTC) Traders in Financial Futures (TFF) report.[5] The brief change in dealer positions from net long to net short is anomalous

[5] The groups are dealers, asset managers (institutional investors, pension funds, insurance companies), leveraged funds (hedge funds), other reportable traders (e.g., corporate treasuries, small banks, or other large financial traders), and so-called "nonreportable" small traders. Since 2010, dealers and asset managers have tended to be long, whereas leveraged funds have tended to be short, suggesting that dealers and asset managers are hedgers and leveraged funds are liquidity suppliers on average. See https://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm.

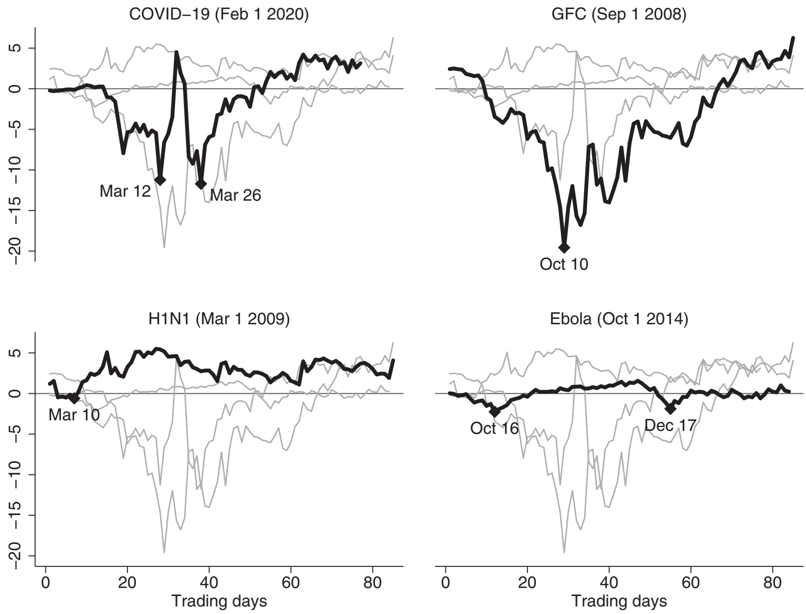

Figure 7
Comparing the COVID-19 pandemic with the Great Financial Crisis, the H1N1 pandemic, and the Ebola outbreak
This figure plots the 1-month VIX premium for the COVID-19 pandemic, the Great Financial Crisis (GFC), the H1N1 pandemic, and the Ebola outbreak. The marked dates indicate the lowest values of the VIX premium in each episode.

in that dealers have historically been net long in this market, with money managers holding short positions.

1.6 Premiums fell in the financial crisis but only slightly in other pandemics

Motivated by the observation that premiums fell as the pandemic and financial conditions worsened, Figure 7 compares the behavior of premiums in the early stages of the COVID-19 pandemic (top-left panel) with the 2008 financial crisis (or "GFC" for "Great Financial Crisis"), H1N1 pandemic, and Ebola pandemic. Figure A1 in the appendix plots the SPX, VIX, VVIX, and long/short strategy trading profits for all four episodes.

The 2008 financial crisis, though not driven by a pandemic, is one of the few market downturns in recent history with a magnitude comparable to the COVID-19 pandemic, and Figure 7 plots the 4 months of VIX premiums starting in September 2008. I choose September 2008 as the start date for the GFC so that a 4-month window covers a brief period immediately before and after the greatest market volatility: the VIX was 22 on September 2, increased to 80 in late October, and gradually declined to 40 by the end of December. The 4-month window matches the 4 months of data (February-May) for the COVID-19 pandemic.

The figure shows that premiums fell negative in the depths of the financial crisis even more than they did in the COVID-19 pandemic. In both episodes, VIX premiums turned negative early on as volatility increased before beginning to recover. On October 10, the VIX reached 70, but the November contract settled at 38, which was 20 points below the fair forecast of the VIX. One caveat, however, is that anomalous negative premiums in the GFC may reflect the much lower liquidity and smaller size of the VIX futures market in 2008 compared to today.

The H1N1 pandemic and the Ebola epidemic occurred within the history of the VIX futures market, and Figure 7 shows that these episodes experienced comparatively minor fluctuations in the VIX premium. Each graph starts on the dates reported in Baker et al. (2020) and examines 4 months of data; Baker et al. (2020) reports 3- and 4-month intervals for the H1N1 pandemic and the Ebola epidemic, respectively. The H1N1 pandemic barely moved estimates of VIX premiums, which stayed positive for nearly the entire duration of the episode. The modest increases in volatility during the Ebola epidemic briefly led premiums to become negative, but the absolute magnitude was relatively small. These patterns are consistent with Jackwerth (2020), who similarly finds no reaction to H1N1 in the risk-neutral distribution of the S&P 500 and a mild reaction to Ebola.

One reason that VIX premiums fell only slightly or not at all in the H1N1 and Ebola episodes may be that these were smaller events for market volatility. Figure A1 in the appendix shows that the VIX continually declined throughout the H1N1 pandemic despite starting at a value above 50 coming out of the financial crisis. For the Ebola epidemic, the VIX averaged 16 and never exceeded 27. The lack of volatility surrounding the two episodes may have set the stage for an underreaction to the COVID-19 pandemic by setting an expectation that the COVID-19 pandemic would play out similarly. Baker et al. (2020) discuss why the market's reaction to the COVID-19 pandemic was so severe compared to a history of epidemics and points to the role of unique policy interventions in restricting economic activity.

1.7 Mispricing or rational pricing?

The descriptive facts above pose a puzzle for standard asset pricing models that incorporate a role for the volatility risk premiums (Bollerslev, Tauchen, and Zhou 2009; Drechsler and Yaron 2011; Eraker and Wu 2017). In these models, volatility or variance risk premiums are always positive and increase with volatility-of-volatility or uncertainty. However, instead of rising in response to COVID-19 risks, VIX premiums initially fell before recovering in late April and May. Moreover, premiums fell so far that they became negative, making futures undervalued in the context of these models.

An important question for future research is to explain why premiums fall to potentially negative levels when risk rises, as the facts above do not distinguish between mispricing or rational pricing under alternative models.

One possible rational explanation is that expectations of bailouts rise as volatility rises, making insurance against unexpected volatility less valuable. Kelly, Lustig, and Van Nieuwerburgh (2016) show that government guarantees in 2008 increased the spread between put options on individual banks and the broader financial sector. More broadly, if unexpected increases in volatility are associated with low marginal utility states, possibly due to positive market jumps ("rare bonanzas"), premiums could be negative.

One possible behavioral explanation is that agents form incorrect expectations about future volatility. Lochstoer and Muir (2019) propose a model where the representative agent relies too much on long lags of volatility to form expectations. As a result, volatility expectations rise insufficiently when volatility rises, and volatility premiums fall. In addition to explaining underreaction to volatility risk, the model explains the ambiguous link between expected stock returns and conditional volatility (French, Schwert, and Stambaugh 1987; Moreira and Muir 2017).

There may be reasons to favor either explanation. All else equal, one reason to favor a rational explanation is that academic studies reduce mispricing (McLean and Pontiff 2016), and the facts above make the COVID-19 pandemic an out-of-sample exemplar of the "low premium-response puzzle" documented in Cheng (2019). On the other hand, evidence in the behavioral literature indicates that investors have biased expectations (e.g., Greenwood and Shleifer 2014).

If negative premiums represent mispricing (in the sense of a deviation from positive equilibrium values), such mispricing may be difficult for arbitrageurs to exploit because of the limits of arbitrage (Gromb and Vayanos 2010). The reason is that the limits of arbitrage may bind more when premiums fall due to increased risk. Such increased risk (e.g., at the end of February) may make arbitrageurs hesitant to go long futures. Furthermore, if the premiums have fallen because of recent increases in risk, arbitrageurs may be effectively more risk averse due to depleted capital from recent losses on short volatility positions. Limits of arbitrage may also hinder cross-market volatility arbitrage (Park 2020).

Finally, ample evidence suggests that fluctuations in hedging demand and liquidity supply affect derivatives prices because of the limits of arbitrage (see, e.g., Acharya, Lochstoer, and Ramadorai 2013; Bollen and Whaley 2004; Cheng, Kirilenko, and Xiong 2015; and Gârleanu, Pedersen, and Poteshman 2009). These fluctuations may help explain underreaction beyond representative agent models. With VIX futures, hedging demand comes from the long side, who pays the VIX premium on average. Figure 6 shows that dealers reduced long positions as risk rose and thus suggests that falling hedging demand may explain concurrent falling premiums, consistent with Cheng

(2019). Dealers may have a time-varying risk appetite, need to hedge exchange-traded products (Todorov 2019), or anticipate future bailouts (Kelly, Lustig, and Van Nieuwerburgh 2016). Time-varying trading motives may be important for understanding time-varying premiums.

2. Historical Evidence

This section considers the COVID-19 pandemic within the history of VIX futures. If there is no similar evidence of underreaction to risk in the history of VIX futures, one might worry that the evidence in the previous section was just a fluke of estimated premiums or unreliable due to the short sample of the pandemic. Evidence from the overall history shows that the underreaction of VIX futures prices during the early stage of the COVID-19 pandemic was a vivid example of broader patterns. The data start in March 2004 and run through May 21, 2020.

2.1 Validating the VIX premium as an estimate of true premiums

If VIX premiums provide information about true premiums, then estimated premiums should systematically forecast VIX futures price movements. I test this idea using the following return forecast regression:

$$xr_t = a + b \ \ VIXR_{t-1} + e_t. \tag{2}$$

The term xr_t is the monthly excess return from a fully collateralized long position in a VIX futures contract; equivalently, xr_t is the unlevered return less a risk-free interest rate earned on margin. The term $VIXR_t$ converts the VIX premium in Equation (1) into a monthly expected excess return.

I take the perspective of an investor who takes a rolling position in the 1-month contract by holding, over every month t, the futures contract expiring in month $t+1$. The investor establishes the position for month t at the end of the month $t-1$ at price F_{t-1}^{t+1} and closes the position at the end of month t at price F_t^{t+1}. For example, in February 2020, the investor would hold the March 2020 contract; in March, the investor would hold the April contract. This roll ensures the position is typically invested in the most liquid contract across the term structure and avoids issues associated with the midmonth final settlement of VIX futures (Griffin and Shams 2018).

Given this perspective, the excess return and expected return in Equation (2) equal:

$$xr_t = \frac{F_t^{t+1}}{F_{t-1}^{t+1}} - 1, \tag{3}$$

$$VIXR_{t-1} = \left(\frac{\widehat{VIX}_{t-1}^{t+1}}{F_{t-1}^{t+1}} \right)^{\frac{21}{n}} - 1, \tag{4}$$

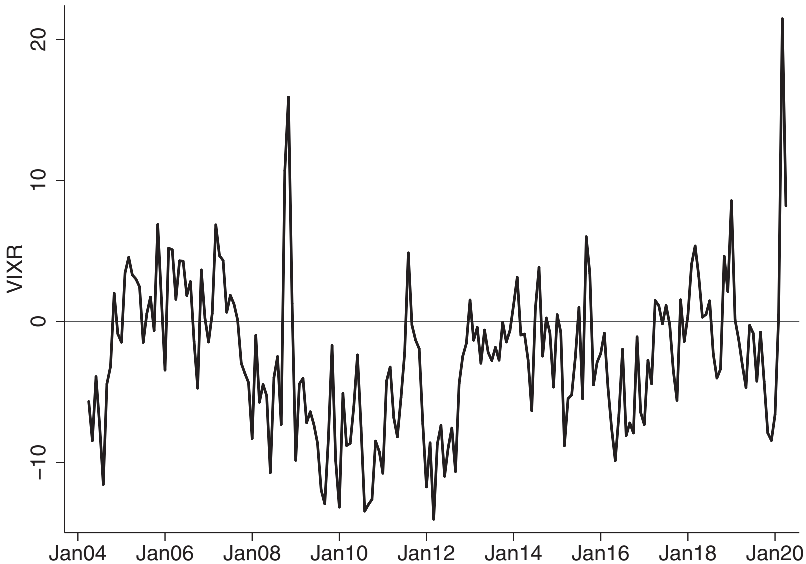

Figure 8
VIXR through time
This figure plots the 1-month VIXR given in Equation (4). VIXR for month t is the expected return of the contract expiring in month t+1, calculated as of the end of month t-1 and expressed in monthly percentage points.

where n is the number of trading days between the end of month $t-1$ and the midmonth futures expiration date in month $t+1$. The scaling factor of $21/n$ rescales the expected return to a 1-month horizon by accounting for the number of such days.

Figure 8 plots $VIXR_t$ through time. On average, it is negative, although there are substantial deviations. From Equations (1) and (4), a negative expected return $VIXR$ corresponds to a positive premium $VIXP$, and a positive expected return $VIXR$ corresponds to a negative premium $VIXP$.

If VIX premium estimates are valid estimates of expected returns, then one expects estimates of b around 1 in Equation (2). In contrast, if the estimates contain significant measurement error, then one expects estimates of b that are statistically indistinguishable from zero or that are even negative. For example, if positive values of $VIXR_{t-1}$ were erroneous and true expected returns are negative, negative values of xr_t would tend to follow positive values of $VIXR_{t-1}$.

Table 4, columns 1–4, report estimates of b close to one (and statistically distinct from zero) and estimates of a close to zero (and not statistically distinct from zero). Columns 1 and 2 report estimates at the monthly frequency and differ by including and excluding the year 2020, respectively. Samples in both columns begin in April 2004, when VIX futures started

Table 4
Predicting VIX futures returns

Dep. var.: Futures return, t	Monthly Full samp. (1)	Monthly Ex. 2020 (2)	Daily Full samp. (3)	Daily Ex. 2020 (4)	Daily 2020-only (5)
b : Slope on VIXR	**1.260**	**0.918**	**1.111**	**0.889**	3.948
	(0.394)	(0.296)	(0.290)	(0.212)	(2.561)
a : Constant	0.090	−1.435	0.031	−0.034	1.199
	(2.003)	(1.680)	(0.091)	(0.072)	(0.880)
T	193	189	4,065	3,967	98
R^2	0.130	0.076	0.007	0.005	0.056

This table reports estimates of Equation (2). The regression forecasts the excess returns of fully collateralized rolling 1-month long VIX futures positions using VIXR. Columns 1 and 2 report estimates at the monthly frequency where returns are measured over month t and VIXR is measured at the end of month t-1. The full sample in column 1 includes months from April 2004 to April 2020, and column 2 excludes the year 2020. Columns 3–5 report estimates at the daily frequency where returns are measured over date t and VIXR is measured at the end of date t-2. Daily data run through May 21, 2020. Returns are expressed as monthly percentage points in columns 1 and 2 and daily percentage points in columns 3–5. The table reports Newey and West (1987) standard errors with 3 lags at the monthly frequency and 22 lags at the daily frequency, except for column 5, which has 5 lags because of the smaller sample. Bold-faced coefficients are statistically distinguishable from zero at the 5% level or lower.

trading. Estimates from the daily data in columns 3 and 4 are close to the monthly estimates. I use a scale factor of $1/n$ in Equation (4) since the exercise predicts daily returns. I use $VIXR_{t-2}$ instead of $VIXR_{t-1}$ to predict xr_t to further ensure that all information would be available in real-time to an investor.

These estimates suggest that, considering all the data, VIX premiums are valid estimates of premiums in the sense that they tend to predict future returns with a coefficient near 1. (Note, however, that like any statistical estimates, they do contain noise.) Columns 2 and 4 suggest that this relationship would have been observable to the market by the end of 2019.

Column 5 reports an estimated coefficient of $b = 4$ considering the year 2020 alone, suggesting that ex post returns during the COVID-19 pandemic were larger than $VIXR$ typically predicted. An investor trading on $VIXR$ would have earned unusually large positive profits in the year 2020, even by the historical standards of the preexisting relationship between $VIXR$ and ex post returns. This insight also explains the relatively larger estimates of b in columns 1 and 3 compared to the estimates that do not include the year 2020 in columns 2 and 4.

These insights hold even though the ARMA statistical model is unlikely to be the optimal VIX forecasting model or the VIX's exact process. This article uses the ARMA model as a baseline because it is well-known, parsimonious, and easy to implement in practice, requiring only the history of the VIX and minor computational resources to estimate. Cheng (2019) shows that, for the relevant horizons considered here, an ARMA(2,2) model forecasts the VIX reasonably well at the relevant monthly horizon when compared with models with other lag structures or direct forecast models that allow for a heterogeneous autoregressive (HAR) structure or other predictors. Undoubtedly, such forecasts can be improved. If anything, the simplicity of the ARMA forecast model should bias against finding that model-derived premium estimates predict ex post returns. As noted above, measurement error should tilt b lower.[6,7]

2.2 Risk-adjusted returns

If VIX premiums provide information about genuine premiums, and premiums fluctuate for reasons unrelated to standard measures of risk, trading strategies based on *VIXP* should generate positive risk-adjusted returns. This section shows that threshold trading strategies that go long or short based on the sign of the premium provide risk-adjusted returns net of transaction costs.

I consider the dynamic "long/short" strategy from Section 1 and test whether putting together both sides of the trade suggested by the signal generates risk-adjusted returns before decomposing the source of returns from each side. Translating the trade from *VIXP* to *VIXR*, the strategy holds long 1-month futures over date t if *VIXR* is greater than zero on date $t-2$ and short futures if *VIXR* is less than zero, with any necessary buy, sell, or roll transactions occurring on date $t-1$. As in Section 1, I assume any transactions occur at bid and ask prices.

The long/short strategy has a risk-adjusted return of 3.4% per month (t-statistic: 2.2) and capital asset pricing model (CAPM) beta of 0.2 over the history of VIX futures. Column 1 of Table 5, panel A, reports these estimates from a standard CAPM performance evaluation regression at the daily frequency. For the market return, I use the total return of the S&P 500. For the risk-free return, I use the return to a 1-month Treasury bill. A 3.4% monthly risk-adjusted return is large; by comparison, equity momentum strategies produce CAPM risk-adjusted returns on the order of 1% per month.

The estimates in column 1 do not distinguish whether the long/short strategy produces risk-adjusted returns by successfully timing long/short positions or by shorting volatility. In general, shorting volatility generates positive CAPM risk-adjusted returns (Coval and Shumway 2001; Bakshi and Kapadia 2003). To better distinguish between the two sources of returns, column 2 reports that the "short/short" strategy that is always short had a risk-adjusted return of 0.8% (t-statistic: 0.8) per month and a CAPM beta of

[6] Internet Appendix Table IA1 reports estimates of ARMA model coefficients. Table IA2 addresses the possibility that negative VIXP estimates are biased downward because of the ARMA model by testing whether the VIX forecast is too high when *VIXP* is negative. The table uncovers no strong evidence of such statistical bias.

[7] Internet Appendix Table IA3 shows that the VIX premium filters out information about expected VIX movements from the futures basis, which is often taken as an "estimation-free" signal of premiums based on the Fama (1984) identity. The futures basis had weakened as a statistical predictor of futures returns by the end of 2019.

Table 5
Risk-adjusted returns

A. Full sample

Dep. var.: Futures return, t	CAPM Long/short (1)	CAPM Short/short (2)	Decomposition Long/short (3)	Decomposition Short/short (4)
a_0 : Alpha	**3.40**	0.80	**2.40**	**2.87**
	(1.52)	(0.96)	(0.96)	(0.94)
a_1 : Differential alpha			−0.01	**-7.55**
			(2.56)	(2.77)
b_0 : Beta	0.18	**2.37**	**2.65**	**2.65**
	(0.31)	(0.22)	(0.19)	(0.19)
b_1 : Differential beta			**-4.75**	−0.53
			(0.38)	(0.32)
T	4,065	4,065	4,065	4,065
R^2	0.00	0.49	0.50	0.50

B. Subsamples

Dep. var.: Futures return, t	Ex. 2020 (1)	2020, Great Financial Crisis, H1N1, and Ebola: 2020-only (2)	GFC (3)	H1N1 (4)	Ebola (5)
a_0 : Alpha	**2.52**	−5.35	4.28	0.19	−10.45
	(0.92)	(17.43)	(3.87)	(7.63)	(6.00)
a_1 : Differential alpha	−1.79	**55.03**	**28.66**	8.61	**18.17**
	(2.25)	(26.85)	(8.90)	(11.43)	(8.48)
b_0 : Beta	**2.73**	1.56	**1.45**	**1.43**	**4.34**
	(0.16)	(1.15)	(0.10)	(0.10)	(0.93)
b_1 : Differential beta	**-4.92**	**-3.38**	**-2.53**	**-2.42**	**-8.89**
	(0.45)	(1.15)	(0.13)	(0.16)	(1.07)
T	3,967	98	252	63	84
R^2	0.51	0.50	0.74	0.75	0.64

Panel A reports estimates of daily CAPM performance regressions and estimates of Equation (5) for the full sample from April 2004 through May 2020. Columns 1 and 2 report estimates of standard CAPM regressions of excess returns as dependent variables on the excess market return. Columns 3 and 4 report estimates of Equation (5), which decomposes returns over periods when VIXR calls for a short or long position. Panel B reports estimates of Equation (5) for the long/short threshold strategy in several subsamples, where "GFC" ranges from September 2008 to August 2009; "H1N1" ranges from March to May 2009; and "Ebola" ranges from October 2014 to January 2015. Units are expressed as monthly percentage points. Panels A and B, column 1, report Newey and West (1987) standard errors with 22 lags; columns 2–5 of panel B use 5 lags. Bold-faced coefficients are statistically distinguishable from zero at the 5% level or lower.

2.4 over the same time period. As will become clear shortly, the risk-adjusted return is not statistically distinguishable from zero because this strategy stays short even when expected returns are positive. The positive beta of shorting volatility is a result of the negative correlation between volatility movements and market returns (French, Schwert, and Stambaugh 1987). Comparing columns 1 and 2 shows that the long/short strategy has a larger point estimate of risk-adjusted return and lower market exposure than the always-short strategy.

To make clearer what is happening, columns 3 and 4 report estimates of the following decomposition of the CAPM regression:

$$xr_t = (a_0 + a_1 1[VIXR_{t-2} > 0]) + (b_0 + b_1 1[VIXR_{t-2} > 0])(r_{M,t} - r_{f,t}) + e_t. \tag{5}$$

This regression decomposes the standard CAPM performance regression into two pieces: the risk-adjusted return and beta when the signal *VIXR* calls for a short position (a_0 and b_0), and the differential return and beta when *VIXR* calls for a long position (a_1 and b_1).

Column 3 shows that the long/short strategy earns positive risk-adjusted returns when it is short and statistically similar risk-adjusted returns when the strategy is long. The risk-adjusted return a_0 when the strategy is short equals 2.4% per month. The differential risk-adjusted long return a_1 is roughly zero, and the standard error is large so that risk-adjusted long returns are statistically indistinguishable from short returns. The standard error of a_1 is large both because positive expected returns are less common and because positive expected returns forecast more volatile returns, as the next subsection shows. Note that the risk-adjusted return in column 1 of 3.4% per month is different than the estimates implied by column 3, and the R^2 value is much lower (almost zero), because the standard CAPM performance regression in column 1 fails to account for the significant time variation in betas noted in column 3.

In contrast, an always-short strategy incurs sizeable average risk-adjusted losses when the *VIXR* signal calls for a long position. Column 4 reports the estimates of Equation (5) for this strategy. It earns a risk-adjusted return a_0 of 2.9% per month when the signal *VIXR* calls for a short position. However, when *VIXR* calls for a long position, the estimate of a_1 indicates that the strategy earns risk-adjusted returns that are 7.6% lower for a risk-adjusted loss of 4.7% during these periods. This pattern helps explain why the always-short strategy did not earn a significant risk-adjusted return in the standard CAPM regression of column 2. The reason is that the strategy was short when estimated expected returns, as measured by *VIXR*, were positive.

Table 5, panel B, reports estimates of the CAPM decomposition in Equation (5) for subsamples. Column 1 excludes the year 2020 and shows that the relationships described above would have been observable to the market by the end of 2019. The point estimate of a_1 is negative, but not statistically distinguishable from zero. Columns 2–5 report estimates for the year 2020-only, 2008 financial crisis, H1N1, and Ebola subsamples. The 2020-only period represents the COVID-19 pandemic. The 2008 financial crisis period starts in September 2008 (as in Figure 2) and covers a full year so that the bottom of the market in March 2009 falls in the middle of the subsample. The H1N1 and Ebola subsamples start and end on the months reported in Baker et al. (2020).

The large point estimates of a_1 in columns 2–5 show that VIX premiums provided valuable signals during the riskiest episodes. Moving from short futures to long futures when *VIXR* turns positive generated extraordinarily large market-adjusted returns in the COVID-19 pandemic (55% per month) and 2008 financial crisis (29% per month) relative to strategies that stayed short, even accounting for the change in beta. (While the table reports standard errors, I focus on describing point estimates given the short samples.) For the crisis, the same caveat as before applies: the VIX futures market was significantly smaller and less liquid in 2008 than it is today. The point estimates for a_1 in H1N1 and Ebola are smaller, likely reflecting the smaller risk spikes and smaller absolute magnitudes of negative premiums in Figure 7.

Altogether, Table 5 suggests that VIX premiums are valuable signals of risk-adjusted returns. Staying short when premiums are negative and expected returns are positive incurs sizeable losses (panel A, column 4). Switching to long futures instead during these periods earns risk-adjusted profits net of transaction costs that are similar in magnitude to the profits from shorting futures when premiums are positive (panel A, column 3). Long futures positions earn these risk-adjusted returns partly through large returns in risky episodes (panel B). Alternatively, the same estimates also suggest that going to cash instead of going long futures when premiums turn negative would sidestep high risk periods that can result in large losses for short futures traders.

Table 6 expands the above exercises to include value, size, investment, profitability, and momentum factors (Fama and French 2015; Jegadeesh and Titman 1993), and the conclusions remain unchanged. The decomposed estimates from Equation (5), appropriately expanded, show that, over the history of the market, the long/short strategy earned positive risk-adjusted returns when it was short and statistically similar risk-adjusted returns when it was long. Risk-adjusted returns during the COVID-19 pandemic and 2008 financial crisis were extraordinarily large, and risk-adjusted returns in the H1N1 pandemic and the Ebola epidemic were comparatively smaller and not statistically distinguishable from zero.

2.3 Systematic underreaction to risk

Aside from just the COVID-19 pandemic, increases in risk systematically tend to move premiums toward lower premiums.

Table 7 examines how premiums *react* to forward-looking measures of risk and how premiums *forecast* future realized risk. If increases in risk systematically push premiums toward lower premiums and higher expected returns, one should see that *VIXR* increases when forward-looking measures of risk increase and that higher *VIXR* forecasts higher subsequent realized risk.

Panel A starts with how premiums react to risk and reports estimates from the following regression:

Table 6
Five-factor risk-adjusted returns.

Dep. var.: Futures ret., t	Full samp. (1)	Ex. 2020 (2)	2020, Great Financial Crisis, H1N1, and Ebola: 2020-only (3)	GFC (4)	H1N1 (5)	Ebola (6)
Alpha	**2.36**	**2.47**	−31.23	4.35	1.19	−9.64
	(0.96)	(0.90)	(15.71)	(4.00)	(8.25)	(8.20)
Diff. alpha	0.66	−1.00	**80.13**	**29.68**	7.94	15.50
	(2.53)	(2.28)	(27.16)	(9.14)	(8.71)	(11.19)
BETA	**2.76**	**2.90**	**1.80**	**1.48**	**1.52**	**3.80**
	(0.20)	(0.13)	(0.67)	(0.14)	(0.20)	(0.91)
SMB	0.07	−0.13	**4.12**	−0.07	−0.22	0.80
	(0.18)	(0.11)	(1.46)	(0.18)	(0.22)	(0.96)
HML	**-0.36**	**-0.30**	**-2.91**	−0.14	−0.07	2.11
	(0.15)	(0.11)	(1.19)	(0.17)	(0.29)	(1.22)
RMW	−0.34	−0.32	**4.10**	**-0.68**	−0.78	−0.59
	(0.25)	(0.17)	(1.80)	(0.34)	(0.80)	(2.04)
CMA	0.15	0.33	−3.25	−0.31	0.06	−2.03
	(0.28)	(0.19)	(3.74)	(0.42)	(0.76)	(2.15)
MOM	**0.34**	**0.41**	0.35	0.04	0.09	0.96
	(0.11)	(0.08)	(1.15)	(0.12)	(0.18)	(0.59)
Diff. BETA	**-4.93**	**-5.23**	**-3.79**	**-2.44**	**-3.78**	**-8.38**
	(0.39)	(0.41)	(0.80)	(0.19)	(0.35)	(1.06)
Diff. SMB	−0.28	0.15	**-5.08**	0.11	**2.05**	−1.03
	(0.36)	(0.32)	(1.58)	(0.29)	(0.39)	(1.40)
Diff. HML	0.29	0.23	**4.32**	−0.08	**1.86**	−4.38
	(0.31)	(0.33)	(1.79)	(0.39)	(0.30)	(2.25)
Diff. RMW	**1.24**	**1.42**	−4.02	0.19	0.93	−1.06
	(0.45)	(0.46)	(2.96)	(0.83)	(1.10)	(3.30)
Diff. CMA	−0.15	−0.80	5.92	0.70		5.14
	(0.76)	(0.62)	(4.96)	(0.73)		(2.93)
Diff. MOM	**-1.26**	**-1.55**	0.69	0.22		−0.95
	(0.31)	(0.27)	(1.58)	(0.35)		(1.50)
T	4,050	3,967	83	252	63	84
R^2	0.52	0.54	0.69	0.75	0.76	0.67

This table reports estimates of daily time-series performance regressions using the Fama and French (2015) five factors plus momentum for the long/short threshold strategy by expanding Equation (5) appropriately. Column 1 reports estimates of for the full sample, and columns 2–6 report estimates for subsamples, where "GFC" ranges from September 2008 to August 2009; H1N1 ranges from March to May 2009; and Ebola ranges from October 2014 to January 2015. Data on factor returns come from Ken French's website and run through April 30, 2020. Units are expressed as monthly percentage points. The table reports Newey and West (1987) standard errors with 22 lags in columns 1 and 2 and 5 lags in columns 3–6. Bold-faced coefficients are statistically distinguishable from zero at the 5% level or lower. The reader should interpret column 5 descriptively given the limited number of dates with negative premiums (positive VIXR) leading to omitted interactions for CMA and MOM.

$$VIXR_t = a + b_0\ \sigma_t + \sum\nolimits_{s=1}^{3} b_s\ \sigma_{t-s} + \sum_{s=1}^{3} c_s\ VIXR_{t-s} + e_t. \qquad (6)$$

In column 1, the risk measure σ_t is the VIX itself, which measures forward-looking volatility in the S&P 500. In column 2, the risk measure σ_t is the VVIX index. The lag structure in Equation (6) allows for dynamics and accounts for any time-series predictability in the VIX premium.

The table reports a positive coefficient on b_0, indicating that increases in risk tend to push premiums lower (expected returns higher). The coefficient b_1 is negative, and the magnitude indicates that the fall in premiums tends to

Table 7
Reaction to risk

A. Reaction to risk

Dep. var.: VIXR, t	Full sample VIX (1)	Full sample VVIX (2)	Ex. 2020 VIX (3)	Ex. 2020 VVIX (4)	2019–2020 VIX (5)	2019–2020 VVIX (6)
b_0: Risk, t	**0.55**	**0.17**	**0.52**	**0.15**	0.87	0.17
	(0.07)	(0.03)	(0.07)	(0.03)	(0.40)	(0.14)
b_1: Risk, t-1	**-0.48**	**-0.11**	**-0.45**	**-0.10**	−0.47	0.03
	(0.08)	(0.02)	(0.08)	(0.03)	(0.25)	(0.12)
b_2: Risk, t-2	−0.07	−0.05	−0.07	−0.05	−0.32	−0.53
	(0.06)	(0.03)	(0.06)	(0.03)	(0.67)	(0.28)
b_3: Risk, t-3	**-0.13**	−0.03	−0.11	−0.02	0.87	0.17
	(0.06)	(0.02)	(0.06)	(0.02)	(0.40)	(0.14)
T	191	167	187	163	16	16
R^2	0.71	0.52	0.71	0.55	0.77	0.59

B. Predicting subsequent risk

Dep. var.: Volatility, t	Full sample S&P 500 (1)	Full sample VIX Fut. (2)	Ex. 2020 S&P 500 (3)	Ex. 2020 VIX Fut. (4)	2019–2020 S&P 500 (5)	2019–2020 VIX Fut. (6)
b_1: VIXR, t-1	**1.10**	**2.07**	**0.47**	**1.37**	**2.54**	**4.18**
	(0.48)	(0.73)	(0.21)	(0.50)	(0.58)	(1.01)
b_2: VIXR, t-2	**-0.60**	**-1.37**	−0.36	**-1.28**	0.79	0.15
	(0.24)	(0.42)	(0.20)	(0.43)	(1.56)	(2.44)
b_3: VIXR, t-3	−0.33	−0.51	−0.11	−0.14	−1.81	−3.46
	(0.23)	(0.54)	(0.15)	(0.42)	(0.98)	(2.42)
T	191	191	187	187	16	16
R^2	0.57	0.17	0.59	0.11	0.83	0.66

Panel A reports estimates of Equation (6). Columns 1 and 2 report estimates for the full sample; columns 3 and 4 reports estimates excluding the year 2020; and columns 5 and 6 report estimates for 2019–2020. In odd-numbered columns, the risk measure is the VIX, and in even-numbered columns, the risk measure is the VVIX. Panel B reports estimates of Equation (7). The regression forecasts monthly return volatility of either the S&P 500 (odd-numbered columns) or the VIX futures (even-numbered) using lags of VIXR and controlling for lags of volatility. Return volatility is expressed as the standard deviation of daily log returns each month expressed as annualized percentage points; VIX and VVIX are also expressed as annualized percentage points. VIXR is expressed as monthly percentage points as in Equation (4). For brevity, the table reports only the b coefficients. The table reports Newey and West (1987) standard errors with three lags, except for the 2019–2020 sample, which includes one lag. The reader should interpret the 2019–2020 results descriptively. Bold-faced coefficients are statistically distinguishable from zero at the 5% level or lower.

reverse after about a month.[8] Columns 3 and 4 repeat this exercise but exclude 2020. Point estimates are slightly smaller, indicating that the COVID-19 pandemic was consistent with or if anything increased the magnitude of the estimated relationship. To show the contribution of the COVID-19

[8] This reversal pattern explains why one-factor models of the premium do not adequately explain the VIX premium (Hu and Jacobs 2020). In their one-factor model of the premium, the premium comoves with the level of the VIX. However, the unconditional correlation of the *level* of VIXP with the *level* of VIX can be positive. Table 7 reveals a puzzling pattern of underreaction in the dynamics, or a “low premium-response” (Cheng 2019), of premiums to risk. In response to increases in the VIX, estimated VIX premiums first fall and then subsequently recover. This can occur even if the unconditional correlation in levels is positive.

pandemic descriptively, columns 5 and 6 report estimates from the 2019–2020 subsample, where I include 2019 to have enough data to estimate Equation (6). The point estimates for b_0 are positive in both cases, and the magnitude of the point estimates suggest that premiums were more sensitive to the VIX during the COVID-19 pandemic than they were historically.

I then turn this exercise around and ask whether lower premiums predict higher *subsequent* realized risk. For example, negative premiums at the end of February 2020 preceded a month of extraordinary volatility, and one can ask whether this pattern is systematic. Panel B reports estimates of the following volatility forecast regression:

$$\sigma_t = a + \sum\nolimits_{s=1}^{3} b_s \ VIXR_{t-s} + \sum_{s=1}^{3} c_s \ \sigma_{t-s} + e_t. \tag{7}$$

The variable σ_t is the standard deviation of daily log returns in month t for the S&P 500 (column 1) or fully collateralized 1-month VIX futures (column 2). The lag structure in Equation (7) accounts for the predictability of volatility.

Columns 1 and 2 of panel B show that the 1-month lag on $VIXR_{t-1}$ positively predicts volatility σ_t for both VIX futures and the S&P 500. This positive predictive relationship b_1 indicates that periods of positive expected returns – that is, periods of negative premiums – tend to presage higher volatility in both VIX futures and the broader market in the next month. Columns 3 and 4 indicate that these relationships were statistically detectable before the year 2020, although at smaller magnitudes. Columns 5 and 6 descriptively show the contribution from the 2019–2020 subsample, where again I include 2019 to have enough data. The point estimates suggest that positive premiums preceded highly risky months during this period, more than had been historically suggested.

Overall, the estimates in Table 7 indicate that VIX premiums underreact to risk, implying that increases in risk push price premiums lower toward negative territory. It is as if a long futures investor pays a smaller expected premium—or, if anything, receives a premium—for hedging uncertainty just when the stock market or VIX futures are about to be very volatile.

3. Conclusion

The underreaction in response to the COVID-19 shock is surprising in that it occurred in the premier market for trading volatility in response to the largest volatility shock in recent history. Future research should explore the reasons for underreaction as it poses a puzzle for standard asset pricing theories. Figure 6 illuminates one potentially important clue: the heterogeneity in the trading behavior among different groups responding to the COVID-19 pandemic. Tables IA4 and IA5 in the Internet Appendix examine this phenomenon more systematically. More broadly, research on financial market responses to pandemics should consider the likelihood that volatility premiums initially underreact to volatility shocks and that different groups of traders may speculate or hedge accordingly.

Appendix

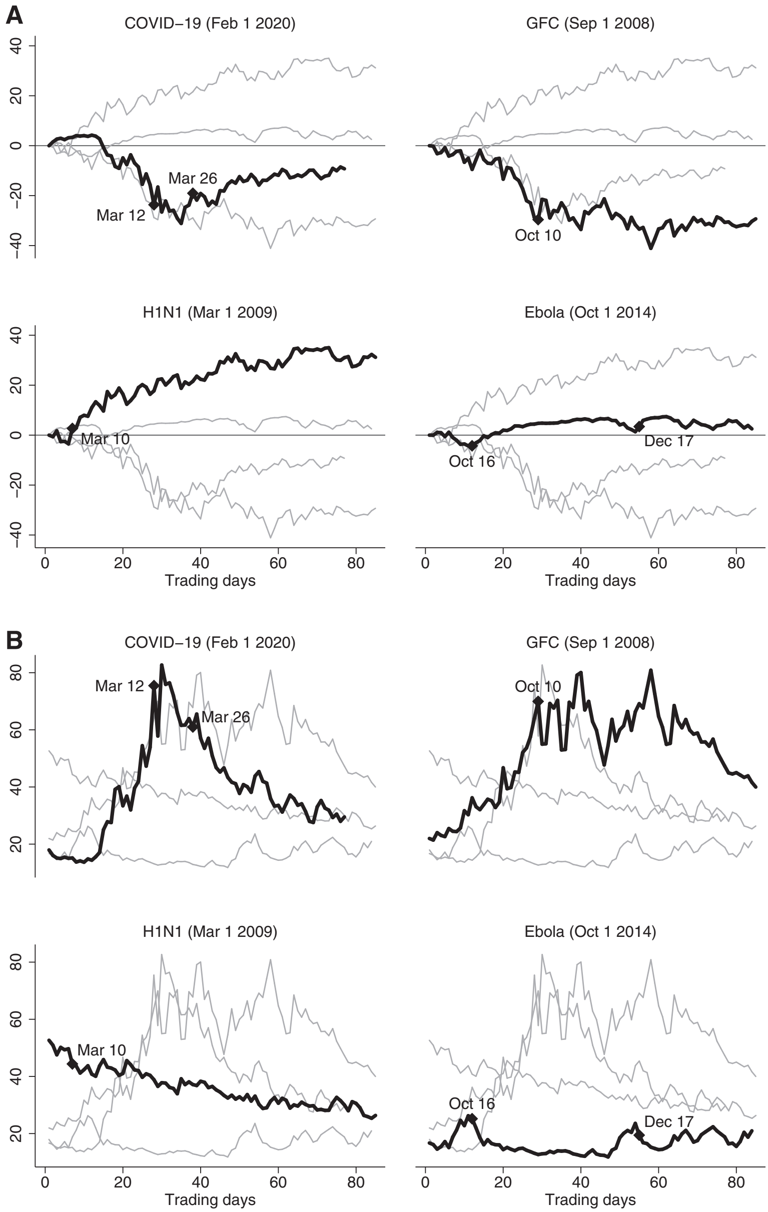

Figure A1

SPX, VIX, and VVIX, trading profits for the COVID-19 pandemic, the Great Financial Crisis, the H1N1 pandemic, and the Ebola epidemic

This figure plots the cumulative SPX percentage price change (panel A), levels of the VIX (panel B), VVIX (panel C), and "long/short" trading profits (panel D) for the COVID-19 pandemic, the Great Financial Crisis (GFC), the H1N1 pandemic, and the Ebola epidemic. Units for vertical axes are all expressed as percentage points. The marked dates indicate the lowest values of the VIX premium in each episode.

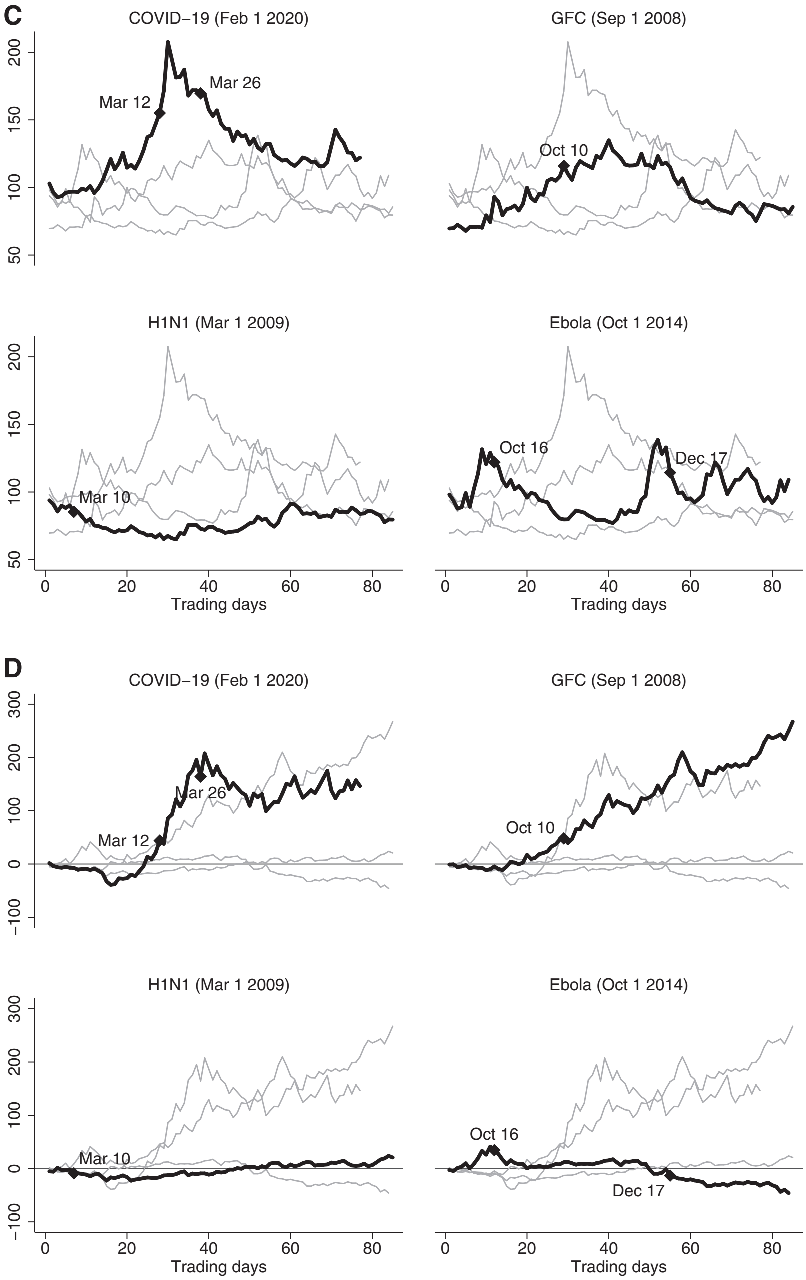

Figure A1
continued

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