Why do option prices predict stock returns?*

Mark Clements Vitali Kalesnik Juhani Linnainmaa†

December 2019

Abstract

Option prices significantly predict stock returns: stocks earn low returns when put options are expensive relative to call options. We attribute most of this predictability to the association between option prices and the conditions in the securities lending market. Writers of put options hedge by shorting the underlying stock; they therefore mark up option prices by the capitalized amount of the expected shorting costs over the life of the option. The implied volatility spread between put and call options aligns with borrowing costs, and this spread predicts changes in future shorting costs. Option prices do not predict stock returns among stocks that are easy to borrow.

NOTE: This is a significantly revised (and incomplete) version of the paper "Older and wiser: The optimal choice of option maturity by informed traders" The original version is available here.

---

*Clements and Kalesnik are with Research Affiliates LLC. Linnainmaa is with the Dartmouth College and NBER. We thank Kenneth Ahern, Rob Arnott, Turan Bali, Chris Brightman, Doug Emery, Gerard Hoberg, Chris Jones, Frank Partnoy, Matthew Ringgenberg, Fan Yu (discussant), and seminar participants at University of Gothenburg, Stockholm University, Lund University, University of Southern California, University of Miami, Indiana University, and University of San Diego 2017 Law and Finance Conference for insightful comments.

†Corresponding author. Mailing address: 100 Tuck Hall, Hanover, NH 03755, United States. E-mail address: Juhani.T.Linnainmaa@tuck.dartmouth.edu, Tel. +1 (603) 646-3160.

1 Introduction

Option prices predict the cross section of equity returns.[1] This predictability is consistent with informed investors trading options to gain leverage (Black 1975) and with stocks being potentially mispriced relative to options when the impediments to arbitrage are large (Miller 1977; Ofek, Richardson, and Whitelaw 2004). In this paper, we first show that long-dated options typically contain all the same information—and more—about equity returns as short-dated options. This result represents a puzzle. Long-dated options are typically very thinly traded. Why do option prices predict stock prices seemingly even in absence of trading?

We show that option prices predict stock returns mostly because option prices are informative about the current and future conditions in the securities lending market. Put option prices, or the quotes of those options in absence of trading, internalize expected shorting costs. An investor writing a put option must account for shorting costs: the option writer must hedge this position by shorting the stock over the life of the option. If shorting is expensive today or expected to be expensive over the life of the option, the writer will price the option higher to cover these costs. Unless the marginal investor is endowed with a short position in the stock—in which case investors would be willing to write put options to hedge—option writers need to be compensated for the expected cost of hedging the options they write.

We show that option prices significantly correlate with the tightness in the securities lending market. When put options are priced similar to the call options—that is, when the spread in their implied volatilities is narrow—the underlying stocks are typically cheap to short. However, among the top decile of stocks with the most expensive put options, the lending fees average more than 5% per year. These fees can be even higher. Among stocks that the market perceives as being the most costly to short, the average annualized fee to short is over 50%, and the average spread in implied

[1] See, for example, Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), Yan (2011), and An, Ang, Bali, and Cakici (2014).

volatilities between put and call options is 47%.

Unless markets are severely fragmented, put option prices must be connected to the expected borrowing costs. Investors seeking to short a stock should be indifferent between a short position in the stock and a synthetic short position created via options. If one market offers a cheaper vehicle for shorting a stock, investors would arbitrage the difference or migrate to that market until the effective costs to short equalize. Consider, for example, the case of Snap Inc. after its IPO in 2017. On July 10, 2017, the short interest in Snap was $1.19 billion, and investors paid an annualized fee of 50 to 60% on their short positions.[2] On the same day, the implied volatility of Snap's one-month at-the-money call options was 51.5%, but that of the put options was 99.5%! Investors seeking to short Snap could therefore either pay the borrowing cost in the securities lending market, or they could pay the expected cost upfront by buying put options; the expected cost of shorting is embedded in the prices of the put options. Because investors can move across the markets, option prices are tied to the current and expected conditions in the securities lending market.

The implied volatility spread between put and call options predicts *changes* in future borrowing costs. When we control for options at different maturities, almost all of the information resides in the prices of long-dated options. This result, which parallels that from the regressions that predict stock returns, also is consistent with the idea that put option prices capitalize difference in borrowing costs. As an option's maturity increases, the capitalized shorting cost is a larger fraction of the option's quoted price; option maturity, in effect, amplifies differences in borrowing costs and makes them easier to detect in option prices. Moreover, if investors can anticipate changes in borrowing costs, such as those occurring around earnings announcements, option prices reflect these expectations even when controlling for today's borrowing costs.

We show that the association between option prices and stock returns is almost entirely due to

[2]See Davies, Megan, 2017, "Investors pay top dollar to short Snap," Reuters, July 11, 2017. We use data from Markit to measure the conditions of the securities lending market. Markit's indicative fee for shorting Snap on July 10, 2017 was 55% and their estimate of the average fee paid by hedge funds was 49.4%.

the association between prices and the conditions of the securities lending market. In Fama-MacBeth regressions, the spread in implied volatilities between put and call options predicts monthly returns with a t-value of -6.01. However, when we control for the cost of borrowing the underlying security, this t-value falls to -2.43. Stocks with expensive put options earn low returns, but these stocks are also the ones with the most binding short-selling constraints; and we know from Jones and Lamont (2002), Ofek, Richardson, and Whitelaw (2004), and others that binding short-selling constraints associate with low average returns. This negative association is consistent with Miller's (1977) overpricing hypothesis: stocks can become overpriced if investors face impediments to shorting stocks. Differences in borrowing costs plausibly induce even the remaining predictive power of option prices; it is just that implied volatilities provide a different (and forward-looking) measure of borrowing costs than the current cost from the securities lending market. Indeed, among stocks that the market perceives as being easy to borrow, we find no reliable association between average returns and option prices; the implied volatility spread has a t-value of -1.12.

Our key results are that, first, long-dated options typically contain all the same information about expected returns as short-dated options and, second, that most (or all) of this predictability is due to option prices measuring differences in expected borrowing costs in the securities lending market. We show, however, that these results, which are clear in the data, would be "easy to miss" because of an additional feature of option prices. Most studies that examine the connection between stock returns and option prices use one-day measures of option prices and implied volatilities. For example, in regressions that predict month $t + 1$ returns, implied volatilities would typically be measured as of the end of month t. This choice seems innocuous: even if there is noise in option prices, similar to that induced by bid-ask spreads, that noise is plausibly inconsequential at the monthly horizon.

We show that, even at the monthly frequency, a liquidity effect massively overstates the predictive power of option prices and obfuscates the association between option prices and borrowing costs. In monthly Fama-MacBeth regressions, end-of-month implied volatility spread predicts returns with a

t-value of -10.67; the implied volatility spread averaged over the last week of the month, skipping a day, predicts returns with a t-value of -6.19. All of this difference is due to a one-day effect: in daily regressions, today's implied volatility spread predicts tomorrow's returns with a t-value of -54.6! This predictability, which does not last beyond one day, is so large that it shows up even at the monthly frequency.

Trading frictions impart this short-term predictability. Suppose, for example, that a stock's value is "known" to be \$100, options are priced based on this valuation, and that the implied volatilities of calls and puts are equal. If a liquidity shock pushes the stock price up to \$101, but options are still based on the \$100 value, what will be the new implied volatility estimates? To justify the price of the call option remaining the same when the price of the underlying increases—the call option should become more valuable—the implied volatility of the call option must fall; and to justify the price of the put option remaining the same when the price of the underlying increases, the implied volatility of the put option must increase. That is, an increase in stock price that is not reflected in the option prices registers as an increase in the implied volatility spread between the put and call options. Here, a positive implied volatility spread predicts low returns because the price will fall back from \$101 to \$100 as the temporary price impact reverses. More generally, if stock price movements that are not matched by movements in option prices are, in part, transitory, then the implied volatility spread must negatively predict returns.

We show that, without correcting for this one-day effect, it will seems as if short-dated options are *more* informative about stock returns than long-dated options, and that option prices significantly predict returns even net of differences in borrowing cost. But all of this additional predictability is due to the one-day microstructure effect. Correcting for this effect, the associations between option prices, borrowing costs, and expected returns become clear.

Our results are consistent with the findings of Ofek, Richardson, and Whitelaw (2004), who show that the violations of the put-call parity in the options market are asymmetric and in the direction of short-sales constraints. They also show that these violations and short-sales constraints predict stock returns; they attribute this predictability to option markets being more efficient than the stock market. Our results extend theirs by showing that long-dated options are more informative about stock returns than short-dated options, and that almost all (or all) of the predictability is due to put option prices capitalizing differences in borrowing costs. Our results are also consistent with An et al.'s (2014) notion about the "joint" cross section of option and stock prices. Option and stock markets must be intimately connected in the absence of a natural supply of put options; unless markets are wildly segmented, it cannot be that the option market provides a way to get around this short-selling constraint. Rather, the prices of put options must adjust so that investors are indifferent between actual and synthetic short positions in stocks. The data are consistent with this mechanism.

Our results do not preclude the possibility that, in some cases, option prices predict returns because informed traders may trade options rather than the stock because of their embedded leverage (Black 1975). Kacperczyk and Pagnotta (2016) study SEC insider trading investigations and find that over 32% of the suspected insider trades take place in options. Moreover, when these putative insiders trade, they account for more than 30% of the daily option trading volume. Options are therefore an important vehicle for informed traders. Augustin, Brenner, Grass, and Subrahmanyam (2016) consider a model in which informed traders optimally choose option types, maturities, and strike prices to maximize the value of their information. Their model is consistent with how investors in the SEC cases actually trade options, and they show that option prices predict returns around corporate events such as mergers. Our result is that, typically and most of the time, option prices predict returns because they serve as proxies for the conditions in the securities lending market.

Our main result is that implied volatility spreads provide a good measure of the tightness of the lending market. It is particularly useful because the cost embedded in the prices of put options is the same cost that would be paid by a would-be arbitrageur looking to hold the short position open in the future. This capitalized cost is not just about the borrowing cost today; it also embeds the risk of shares being recalled and the risk of borrowing costs changing in the future (Engelberg, Reed, and Ringgenberg 2018).

2 Data

2.1 CRSP and Compustat

We use monthly and daily return data on stocks listed on NYSE, AMEX, and Nasdaq from the Center for Research in Securities Prices (CRSP). We include only ordinary common shares (share codes 10 and 11). We use CRSP delisting returns; if a delisting return is missing and the delisting is performance-related, we impute a return of -30% for NYSE and AMEX stocks and -55% for Nasdaq stocks.[3]

We obtain accounting data from annual Compustat files to compute book-to-market ratios. We lag accounting information by six months to ensure that this information is known to investors (Fama and French 1993). For example, if a firm's fiscal year ends in December in year t, we assume that this information is available to investors at the end of June in year $t + 1$. We compute a firm's book-to-market ratio as the book value of equity divided by the December market value of equity.

2.2 OptionMetrics

We take daily implied volatilities from the implied volatility surface file provided by OptionMetrics. This file contains implied volatilities for calls and puts with standardized strike prices and maturities. OptionMetrics constructs these surfaces by interpolating implied volatilities computed from individual options; a point on the surface is included only if there are enough options near this point. Because OptionMetrics recomputes this surface in real time every day, it does not have a

[3]See Shumway (1997) and Shumway and Warther (1999).

lookahead bias (An et al. 2014). OptionMetrics values options and extracts implied volatilities using a binomial tree model that accounts for dividends and early exercise.

We also use the daily price file from OptionMetrics to measure open interest and trading volume. These data detail the daily closing quotes of all options written on each stock and provide open interest and trading volume information. OptionMetrics data begin in January 1997.

2.3 Markit

We take securities lending market information from Markit. These data, which begin in 2006, contain information on the conditions of the securities lending market. We use information on indicative fees, simple average fees from stock borrow transactions, and the cost of borrow scores. Markit data begin in July 2006 except for the average fees from stock borrow transactions, for which the data begin in April 2007.

2.4 Summary statistics

Panel A of Table 1 shows how the options and lending market coverage varies by firm size. The sample period is from January 1996 through September 2019, which is the period covered by OptionMetrics. We sort firms into deciles using NYSE market capitalization breakpoints and report the fraction of firms with listed options. In the bottom decile, only 15% of firms have any listed options; in the top decile the coverage is 98%. The coverage in the lending market, according to Markit, is better. The fraction of securities with information about the conditions in the lending market ranges from 84% in the bottom decile to 97% in the top decile. Because we examine the predictability of equity returns using option prices, we limit the sample throughout this study to firms with listed options. Later, when we examine the associations between option prices, borrowing costs, and returns, we furthermore limit the sample to the post-2006 period, which is the period covered by Markit.

REFERENCES

An, B.-J., A. Ang, T. G. Bali, and N. Cakici (2014). The joint cross section of stocks and options. *Journal of Finance 69*(5), 2279–2337.

Augustin, P., M. Brenner, G. Grass, and M. G. Subrahmanyam (2016). How do informed investors trade in the options market? Working paper.

Bali, T. G. and A. Hovakimian (2009). Volatility spreads and expected stock returns. *Management Science 55*(11), 1797–1812.

Black, F. (1975). Fact and fantasy in the use of options. *Financial Analysts Journal 31*(4), 36–41, 61–72.

Black, F. and M. Scholes (1973). The pricing of options and corporate liabilities. *Journal of political economy 81*(3), 637–654.

Cremers, M. K. J. and D. Weinbaum (2010). Deviations from put-call parity and stock return predictability. *Journal of Financial and Quantitative Analysis 45*(2), 335–367.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg (2018). Short-selling risk. *Journal of Finance 73*(2), 755–786.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Goyal, A. and A. Saretto (2009). Cross-section of option returns and volatility. *Journal of Financial Economics 94*(2), 310–326.

Hasbrouck, J. (2009). Trading costs and returns for us equities: Estimating effective costs from daily data. *Journal of Finance 64*(3), 1445–1477.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance 45*(3), 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance 48*(1), 65–91.

Jones, C. M. and O. A. Lamont (2002). Short sale constraints and stock returns. *Journal of Financial Economics 66*, 207–239.

Kacperczyk, M. T. and E. Pagnotta (2016). Chasing private information. Working paper.

Kaniel, R., S. Liu, G. Saar, and S. Titman (2012). Individual investor trading and return patterns around earnings announcements. *Journal of Finance 67*(2), 639–680.

Kaniel, R., G. Saar, and S. Titman (2008). Individual investor trading and stock returns. *Journal of Finance 63*(1), 273–310.

Kelley, E. K. and P. C. Tetlock (2013). How wise are crowds? Insights from retail orders and stock returns. *Journal of Finance 68*(3), 1229–1265.

Kelley, E. K. and P. C. Tetlock (2017). Retail short selling and stock prices. *Review of Financial Studies 30*(3), 801–834.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *Journal of finance 32*(4), 1151–1168.

Nagel, S. (2012). Evaporating liquidity. *Review of Financial Studies 25*(7), 2005–2039.

Novy-Marx, R. and M. Velikov (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies 29*(1), 104–147.

Ofek, E., M. Richardson, and R. F. Whitelaw (2004). Limited arbitrage and short sales restrictions: Evidence from the options markets. *Journal of Financial Economics 74*(2), 305–342.

Pan, J. and A. M. Poteshman (2006). The information in option volume for future stock prices. *Review of Financial Studies 19*(3), 871–908.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance 39*(4), 1127–1139.

Shumway, T. (1997). The delisting bias in CRSP data. *Journal of Finance 52*(1), 327–340.

Shumway, T. and V. A. Warther (1999). The delisting bias in CRSP's Nasdaq data and its implications for the size effect. *Journal of Finance 54*(6), 2361–2379.

Stoll, H. R. (1969). The relationship between put and call option prices. *Journal of Finance 24*(5), 801–824.

Xing, Y., X. Zhang, and R. Zhao (2010). What does the individual option volatility smirk tell us about future equity returns? *Journal of Financial and Quantitative Analysis 45*(3), 641–662.

Yan, S. (2011). Jump risk, stock returns, and slope of implied volatility smile. *Journal of Financial Economics 99*(1), 216–233.

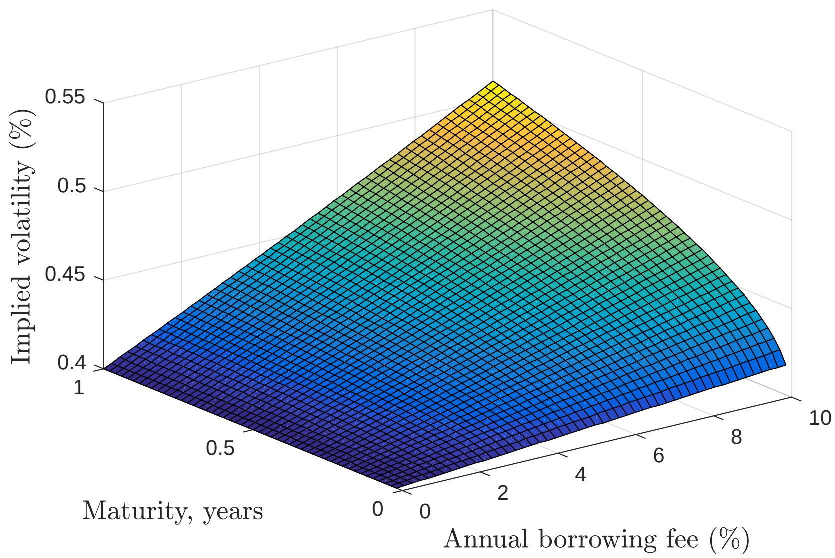


Figure 1: **Implied volatility, time to maturity, and borrowing fee.** This figure plots implied volatility of put options as a function of option maturity and the borrowing cost in the securities lending market. We price European-style options using the Black-Scholes model with $S = 100$, $K = 100$, $r_f = 2\%$, and $\sigma = 40\%$. Time to maturity varies from one week to one year and the shorting cost from 0% to 10% per year. We capitalize the expected cost to short the option as $B = (e^{b \times T} - 1) \times |\Delta| \times S$, where T is time to maturity, b is the annualized borrowing cost, Δ is the put option's delta, and S is the current share price. This computation assumes a constant shorting cost. This figure plots implied volatility computed from the Black-Scholes price of the option plus the capitalized shorting cost, B.

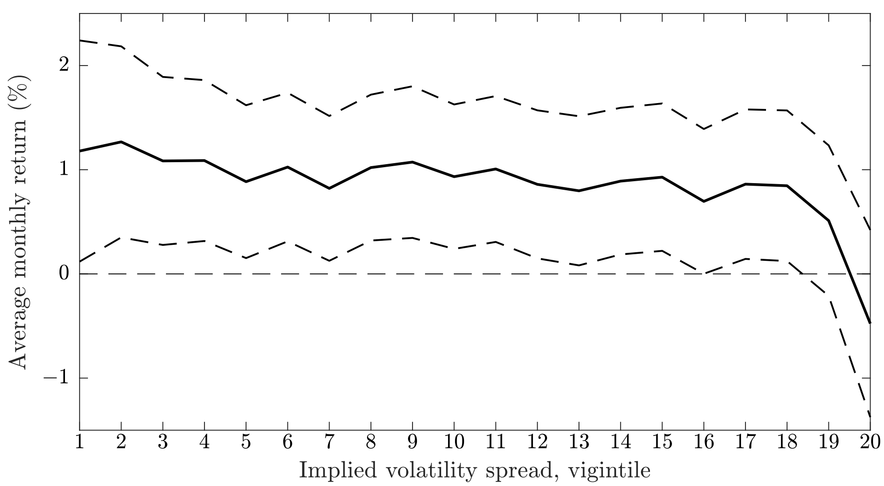
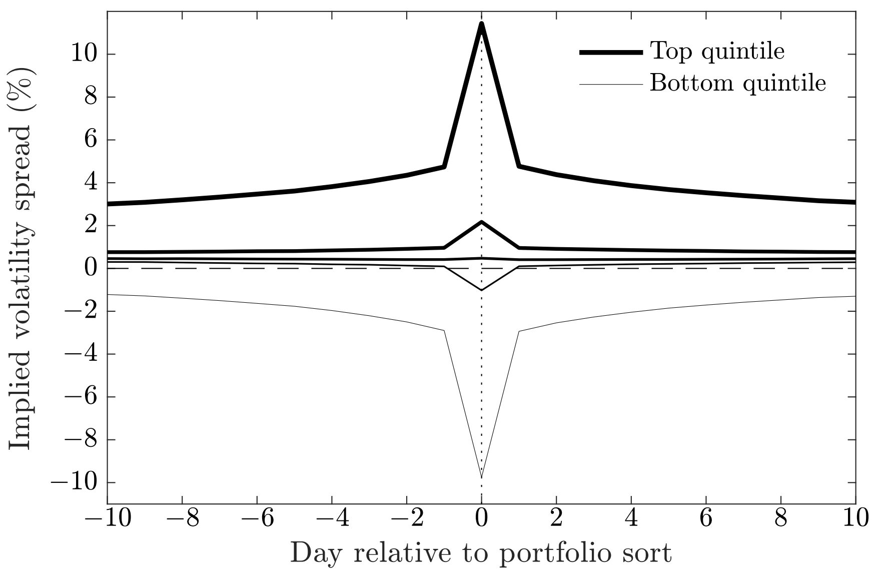


Figure 2: **Return asymmetry in portfolios sorted by the implied volatility spread between put and call options.** We sort stocks into 20 portfolios (vignettes) by the spread in implied volatilities between put and call options at the end of each month t and compute equal-weighted average returns for these portfolios in month $t+1$. The dashed lines denote the 95% confidence interval.



Day d quintile	Day $d+1$ quintile: Low	2	3	4	High
Low	41%	16%	11%	13%	19%
2	16%	29%	26%	20%	10%
3	11%	26%	32%	23%	9%
4	13%	20%	23%	28%	17%
High	19%	10%	9%	17%	46%

Figure 3: **Implied volatility spreads around portfolio formation.** We sort stocks into quintiles each day by implied volatility spread and plot the average implied volatility spread, Put−Call IV, for each quintile for a 20-day period surrounding the date of the portfolio sort. The transition matrix below the figure reports the probability that a stock assigned to quintile q on day d is assigned to quintile q' on day $d+1$.

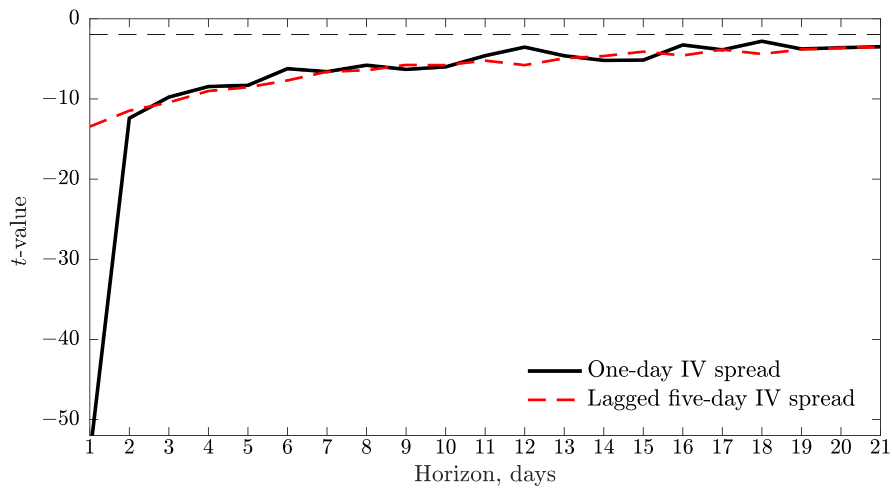


Figure 4: **Predicting the cross section of daily equity returns.** This figure reports t-values from cross-sectional regressions that predict daily equity returns. The x-axis indicates the horizon in days; horizon $= 5$, for example, predicts the cross section of day $d + 5$ returns using variables measured at the end of trading day d. The first set of regressions predict returns using today's implied volatility spread. The second set of regressions uses the five-day average implied volatility spread lagged by one day. Both sets of regressions include day t stock return, log-size, log-book-to-market as additional regressors. Implied volatilities are measured from one-month at-the-money options. The dashed horizontal line represents the 5% critical threshold ($t = -1.96$).

Table 1: Options and securities lending market coverage, 1996–2019

This table reports on the options and securities lending market coverage. In Panel A we assign stocks into deciles by NYSE market capitalization distribution and report the fraction of firms with listed options and with securities lending market information from Markit. We also report the number of firms and the mean and median market values. We form the deciles each month, compute coverage and mean and median market values, and then report the time-series averages of these statistics. OptionMetrics data begin in 1996; Markit data for the securities lending market begin in 2006. Both data end in September 2019. Panel B reports average implied volatilities of at-the-money call and put options for one-, three-, six-, and twelve-month maturities. It also reports the average historical volatility, computed using six months of daily returns. Implied volatility spread is the difference in the implied volatilities between put and call options.

Classification	Size decile	Number of firms	Fraction with listed options	Market value, billions: Mean	Market value, billions: Median	Lending market
All-but-Microcaps	10 (big)	177.6	97.6%	58.48	34.00	97.0%
	9	190.8	97.2%	11.26	10.75	96.3%
	8	204.1	94.1%	5.49	5.35	96.0%
	7	217.5	89.1%	3.25	3.20	96.2%
	6	236.9	85.5%	2.14	2.12	96.2%
	5	278.3	81.8%	1.44	1.42	96.1%
	4	337.3	73.9%	0.95	0.94	95.5%
	3	426.3	64.2%	0.59	0.59	95.0%
Microcaps	2	651.8	49.0%	0.32	0.31	93.2%
	1 (small)	2,150.2	15.2%	0.08	0.06	84.0%
All-but-Microcaps		2,068.9	81.8%	7.88	1.79	95.9%
Microcaps		2,802.0	23.3%	0.14	0.10	86.2%

Table 2: Implied volatilities of call and put options

This table reports average implied volatilities of at-the-money call and put options with one-, three-, six-, and twelve-month maturities. Implied volatility spread is the difference in the implied volatilities of at-the-money put and call options. Realized volatility is the annualized volatility of daily returns computed using six-months of data.

Option	Average implied volatility (%)			
maturity	Put	Call	Put−Call	t(Put−Call)
30 days	49.8	49.1	0.8	13.32
91 days	48.2	47.2	1.1	26.27
182 days	47.3	46.1	1.2	30.24
365 days	47.0	45.7	1.3	30.24
	Average (%)			
Realized volatility	47.4			

Option	Put-Call IV spread (%), percentiles				
maturity	10th	25th	50th	75th	90th
30 days	−3.7	−0.8	0.5	2.1	5.4
91 days	−2.0	−0.3	0.5	1.9	4.6
182 days	−1.6	−0.2	0.6	2.0	4.7
365 days	−1.7	−0.3	0.7	2.2	5.0

Table 3: Predicting the cross section of stock returns with implied volatility spreads

This table reports average regression slopes and their t-values from cross-sectional regressions that predict month $t+1$ returns using the spread in implied volatilities of at-the-money put and call options. Implied volatility spreads are measured using one-, three-, and six-month options. The sample consists of firms with positive book values of equity and traded options. The return data are from February 1996 through September 2019.

Explanatory variable	Regression model (1)	(2)	(3)	(4)	(5)	(6)
log(ME)	−0.14	−0.13	−0.13	−0.13	−0.13	−0.13
	(−3.06)	(−2.96)	(−2.90)	(−2.94)	(−2.89)	(−2.87)
log(BE/ME)	0.00	0.00	0.00	0.00	0.00	0.00
	(−0.02)	(−0.01)	(−0.00)	(−0.03)	(−0.01)	(−0.03)
r_1	−1.45	−1.44	−1.43	−1.43	−1.42	−1.40
	(−2.84)	(−2.84)	(−2.82)	(−2.81)	(−2.80)	(−2.77)
$r_{12,2}$	0.19	0.19	0.19	0.19	0.19	0.19
	(1.00)	(1.02)	(1.03)	(1.03)	(1.03)	(1.03)
Realized volatility	−2.03	−2.00	−1.98	−1.99	−1.97	−1.97
	(−2.75)	(−2.71)	(−2.68)	(−2.70)	(−2.67)	(−2.67)
Implied volatilities						
Realized minus implied volatility	1.68	1.65	1.64	1.66	1.65	1.66
	(3.50)	(3.44)	(3.43)	(3.43)	(3.43)	(3.43)
Put IV − Call IV						
30-day options	−2.86			−0.12		−0.25
	(−6.19)			(−0.20)		(−0.44)
91-day options		−4.24		−4.23	−0.55	−0.32
		(−7.58)		(−5.74)	(−0.60)	(−0.31)
182-day options			−5.14		−4.78	−4.89
			(−8.46)		(−4.48)	(−4.60)

Table 4: Distribution of option trading volume and open interest by maturity

This table reports on the availability of options and the distribution of trading volume and open interest by maturity. We compute, for each day and stock, the fraction of trading volume and open interest in call and put options with maturities ranging from one month to over a year. We compute the average percentages each day across the stocks. This table reports the time series averages of these distributions. Column "Options exist" is the average fraction of stocks with positive open interest or trading volume. This table uses daily option volume data from January 1996 through September 2019. The sample consists of all-but-microcap firms with at least one listed option at any maturity.

		Trading volume		Open interest	
Option maturity	Options exist	Call options	Put options	Call options	Put options
0–1 month	93.8%	32.8%	35.7%	27.6%	27.5%
1–2 months	91.2%	24.4%	24.6%	19.8%	19.2%
2–3 months	34.8%	8.8%	7.9%	15.3%	14.9%
3–4 months	34.9%	7.9%	7.1%	10.6%	10.5%
4–5 months	34.6%	7.3%	6.4%	9.1%	9.2%
5–6 months	32.7%	6.8%	5.9%	7.0%	7.3%
6–7 months	34.1%	5.1%	4.9%	3.7%	4.0%
7–8 months	32.5%	3.7%	3.9%	1.7%	1.8%
8–9 months	3.1%	0.4%	0.5%	0.6%	0.7%
9–10 months	2.3%	0.3%	0.3%	0.6%	0.6%
10–11 months	2.3%	0.3%	0.3%	0.6%	0.6%
11–12 months	2.2%	0.3%	0.3%	0.5%	0.6%
Over 12 months	23.2%	2.0%	2.3%	2.8%	3.0%

Table 5: Option prices and borrowing costs in the securities lending market

This table reports average borrowing costs for stocks sorted by the implied volatility spread between put and call options (Panel A) or the cost of borrowing score (Panel B). In Panel A stocks are assigned into deciles; in Panel B the assignment is based on the score provided by Markit. “Difficult to borrow” is an indicator variable set to one for firms with a cost of borrowing score greater than one and zero otherwise. The data begin in July 2006 except for the average hedge fund fee for which the data begin in April 2007.

Panel A: Stocks sorted by implied volatility spread between put and call options

IV Spread Decile	Cost of Difficult score	borrowing to borrow	Indicative fee (%)	Hedge fund average fee (%)
Low	1.37	15.1%	1.21	0.98
2	1.11	5.1%	0.60	0.49
3	1.05	2.7%	0.51	0.40
4	1.05	2.3%	0.49	0.39
5	1.05	2.8%	0.49	0.39
6	1.07	3.7%	0.53	0.42
7	1.11	5.7%	0.59	0.48
8	1.17	8.8%	0.73	0.57
9	1.36	16.2%	1.11	0.87
High	3.24	49.3%	8.09	6.09

Panel B: Stocks sorted by the cost of borrowing score

Cost of Borrowing Score	Average number of firms	Implied volatility spread (%)	Indicative fee (%)	Hedge fund average fee (%)
Low	2,022.8	0.5	0.4	0.3
2	89.9	1.4	1.6	1.7
3	46.8	2.9	3.5	3.2
4	33.2	4.7	6.3	5.3
5	22.9	6.8	8.6	7.6
6	18.2	9.0	11.2	10.5
7	17.4	13.0	15.5	14.2
8	9.8	17.7	22.5	19.6
9	9.6	23.9	30.5	25.7
High	14.1	46.6	60.0	50.9

Table 6: Future borrowing costs and implied volatility spreads

This table predicts average slope coefficients and t-values from cross-sectional regressions to predict the difficulty of borrowing in month $t+1$ (Panel A) or $t+2$ (Panel B). The dependent variable is "difficult to borrow," which is an indicator variable set to one if the Markit cost of borrowing score is greater than one and to zero otherwise. The explanatory variables are implied volatility spreads of one-, three-, and six-month options, and the difficult to borrow in month t. The data begin in July 2006.

Panel A: Predicting month $t+1$ difficulty of borrowing

Explanatory variable	Regression (1)	(2)	(3)	(4)
Put IV − Call IV				
30-day options	0.07			0.00
	(8.77)			(−0.18)
91-day options		0.12		0.02
		(11.98)		(1.41)
182-day options			0.14	0.13
			(12.87)	(9.29)
Difficult to borrow	0.87	0.87	0.86	0.86
in month t	(155.12)	(149.80)	(148.08)	(147.73)

Panel B: Predicting month $t+2$ difficulty of borrowing

Explanatory variable	Regression (1)	(2)	(3)	(4)
Put IV − Call IV				
30-day options	0.09			0.00
	(9.71)			(0.27)
91-day options		0.15		0.03
		(12.09)		(2.22)
182-day options			0.18	0.15
			(14.06)	(11.03)
Difficult to borrow	0.83	0.82	0.82	0.82
in month t	(138.88)	(132.57)	(130.72)	(130.40)

Table 7: Predicting the cross section of stock returns with implied volatility spreads

This table reports average regression slopes and their t-values from cross-sectional regressions that predict month $t+1$ returns using the spread in implied volatilities of six-month at-the-money put and call options. Difficult to borrow is an indicator variable set to one if the Markit cost of borrowing score is greater than one and to zero otherwise. The sample in the last column consists of stocks that have a cost of borrowing score of one. The sample consists of firms with positive book values of equity, traded options, and information on the securities lending market. The return data are from August 2006 through September 2019.

Explanatory variable	Regression model (1)	(2)	(3)	(4)	(5)	Easy to short
Put IV − Call IV,	−4.51		−3.74	−1.95	−1.76	−0.79
182-day options	(−6.01)		(−5.19)	(−2.68)	(−2.43)	(−1.12)
Difficult to borrow		−1.02	−0.77			
		(−5.25)	(−4.20)			
Borrowing cost score, 2				−0.35		
				(−1.74)		
3				−0.70		
				(−2.05)		
4				−0.79		
				(−2.19)		
5				−1.01		
				(−2.26)		
6				−1.01		
				(−2.16)		
7				−1.64		
				(−3.09)		
8				−2.82		
				(−3.78)		
9				−2.43		
				(−2.45)		
High				−4.20		
				(−5.78)		
Indicative fee					−9.03	
					(−7.15)	

Table 8: Predicting the cross section of stock returns with end-of-month implied volatility spreads

This table reports average regression slopes and their t-values from cross-sectional regressions that predict month $t+1$ returns using the spread in implied volatilities of at-the-money put and call options. Implied volatility spreads are measured using one-, three-, and six-month options. These regressions are similar to those reported in Table 3 except that the implied volatilities are measured as of the last trading day of month t. Panel A compares the predictive power of one-, three-, and six-month options; Panel B controls for the conditions in the securities lending market. The return data in Panel A are from February 1996 through September 2019; those in Panel B are from August 2006 through September 2019.

Panel A: Comparing one-, three-, and six-month implied volatility spreads

Explanatory variable	**Regression model** (1)	(2)	(3)	(4)	(5)	(6)
log(ME)	−0.13	−0.12	−0.12	−0.12	−0.12	−0.12
	(−2.80)	(−2.70)	(−2.67)	(−2.73)	(−2.64)	(−2.68)
log(BE/ME)	0.01	0.01	0.01	0.01	0.01	0.01
	(0.16)	(0.16)	(0.17)	(0.14)	(0.17)	(0.15)
r_1	−1.42	−1.40	−1.40	−1.37	−1.39	−1.36
	(−2.80)	(−2.76)	(−2.78)	(−2.71)	(−2.74)	(−2.69)
$r_{12,2}$	0.19	0.19	0.19	0.19	0.19	0.19
	(1.02)	(1.02)	(1.02)	(1.02)	(1.02)	(1.03)
Realized volatility	−1.88	−1.88	−1.88	−1.87	−1.87	−1.85
	(−2.60)	(−2.60)	(−2.60)	(−2.58)	(−2.58)	(−2.56)
			Implied volatilities			
Realized minus implied volatility	1.34	1.33	1.35	1.33	1.33	1.33
	(2.92)	(2.92)	(2.96)	(2.91)	(2.92)	(2.90)
Put IV − Call IV						
30-day options	−3.81			−2.19		−2.16
	(−10.67)			(−5.18)		(−5.11)
91-day options		−4.93		−2.94	−3.12	−1.28
		(−10.86)		(−5.28)	(−4.06)	(−1.58)
182-day options			−5.47		−2.61	−2.46
			(−10.98)		(−3.15)	(−2.96)

Panel B: Controlling for securities lending market conditions

Explanatory variable	All stocks	Easy to short
log(ME)	−0.05	−0.05
	(−1.05)	(−0.98)
log(BE/ME)	−0.13	−0.15
	(−1.59)	(−1.92)
r_1	−0.95	−0.89
	(−1.42)	(−1.25)
$r_{12,2}$	−0.19	−0.26
	(−0.67)	(−0.90)
Realized volatility	−0.41	−0.23
	(−0.57)	(−0.30)
Realized minus implied volatility	0.16	−0.19
	(0.43)	(−0.53)
Put IV − Call IV, 182-day options	−1.58	−1.47
	(−3.51)	(−3.03)
Indicative fee	−9.12	
	(−6.45)	

Table 9: Long-term stock returns and end-of-month and average implied volatility spreads

This table reports average regression slopes and their t-values from cross-sectional regressions that predict month $t+1$ returns using the spread in implied volatilities of six-month at-the-money put and call options. We measure implied volatilities either as of the end of month t or as the average implied volatility spread over the last five trading days of month t, skipping a day. In regressions that predict returns from month $t+2$ to month $t+6$ and from month $t+7$ to month $t+12$, we reorganize the data as in Jegadeesh and Titman (1993) to avoid the use overlapping data. The return data are from February 1996 through September 2019.

Explanatory variable	Predictive horizon: Month $t+1$		$t+2$ to $t+6$		$t+7$ to $t+12$	
log(ME)	−0.13	−0.14	−0.07	−0.07	−0.05	−0.06
	(−2.79)	(−3.06)	(−1.61)	(−1.61)	(−1.12)	(−1.27)
log(BE/ME)	0.01	0.00	0.01	0.01	−0.01	−0.01
	(0.12)	(−0.02)	(0.18)	(0.14)	(−0.10)	(−0.18)
r_1	−1.38	−1.45	0.52	0.54	0.35	0.37
	(−2.73)	(−2.84)	(1.56)	(1.62)	(1.34)	(1.42)
$r_{12,2}$	0.19	0.19	0.03	0.04	−0.07	−0.07
	(1.04)	(1.00)	(0.23)	(0.25)	(−0.82)	(−0.81)
Realized volatility	−1.89	−2.03	−1.45	−1.43	−0.91	−0.95
	(−2.60)	(−2.75)	(−1.98)	(−1.92)	(−1.20)	(−1.24)
Implied volatilities						
Realized minus implied volatility	1.34	1.68	1.04	1.08	0.51	0.66
	(2.90)	(3.50)	(2.44)	(2.36)	(1.14)	(1.39)
Put IV − Call IV						
End-of-month	−3.86		−0.91		−1.08	
	(−10.60)		(−4.77)		(−5.50)	
Average		−2.86		−1.97		−2.41
		(−6.19)		(−5.80)		(−7.02)