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Monetary policy communication, policy slope, and the stock market[☆]

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ABSTRACT

The slope factor is constructed from changes in federal funds futures of different horizons and predicts stock returns at the weekly frequency: faster policy easing positively predicts returns. It contains information about the speed of future monetary policy tightening and loosening, and predicts changes in interest rates and forecast revisions of professional forecasters. The tone of speeches by FOMC members correlates with the slope factor. The predictive power concentrates in times of high uncertainty in line with the pre-FOMC announcement drift. Our findings show the path of interest rates matters for asset prices, and monetary policy affects asset prices continuously.

1. Introduction

The main objectives of the Federal Reserve (Fed) under its dual mandate are price stability and maximum employment. The fed funds rate is the Fed's main conventional policy tool to achieve those goals. But whereas real consumption, investment, and GDP only respond with a lag to changes in the target rate, a large literature documents that asset prices respond directly and immediately to monetary policy in narrow event windows around Federal Open Market Committee (FOMC) rate changes (see Bernanke and Kuttner, 2005). Yet asset prices might react not only to changes in short-term interest rates, but also to changes in expectations about the speed of monetary policy loosening and tightening, in the words of former Chairwomen Yellen: "The FOMC will, of course, carefully deliberate about when to begin the process of removing policy accommodation. But the significance of this decision should not be overemphasized, because what matters for financial conditions and the broader economy is the entire expected path of short-term interest rates and not the precise timing of the first rate increase." Moreover, monetary policy decisions happen throughout the year rather than only on eight

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scheduled FOMC meetings that are the focus of a large event-study literature as stressed by former governor Warsh: "Policy deliberations happen on a rather continuous basis." Finally, former Chairman Bernanke emphasizes "monetary policy is 98% talk and only 2% action."

We use weekly changes in the one-month and three-month federal funds futures-implied rates to test for the effect of changes in the future path of monetary policy on asset prices throughout the year.[1] Specifically, we argue that changes in one-month futures, $ff_{t,1}$, affect all future target rates, and we can interpret it as a level factor. Changes in the three-month futures, $ff_{t,3}$, instead also contain information about the future path of monetary policy. We regress changes in the three-month futures-implied rate on the changes in the one-month futures-implied rate to get a purified measure of changes in expectations of the path of future monetary policy. We refer to the residual of this regression as the *slope factor* or simply slope. Slope robustly predicts excess returns of the Center for Research in Security Prices (CRSP) value-weighted index over the following week and explains around 2% of the weekly variation in stock returns. The predictive power is especially strong in times of heightened market uncertainty as proxied by the VIX which is also the time during which the pre-FOMC announcement drift of Lucca and Moench (2015) is most significant.

A positive slope, that is, expectations of faster future monetary policy tightening, predict negative stock returns. Excluding weeks with FOMC meetings does not change the predictability which is stable throughout the year. In fact, we find speeches of the chair or vice chair – which only occur outside of the blackout periods before FOMC meetings – systematically predict the slope factor consistent with the Bernanke hypothesis.

Our findings suggest that the whole future path of monetary policy is important for the real economy and that the FOMC releases most of the news about monetary policy outside of scheduled FOMC meetings throughout the year. This interpretation is consistent with evidence in Gorodnichenko and Weber (2016) who document most monetary policy shocks within narrow event windows around FOMC decisions are tiny. Our findings open up exciting new avenues for future research. Through which channels do future changes in target rates matter for financial markets, such as a risk-free rate, inflation, or risk-premium channel? How does the FOMC communicate and transmit news about monetary policy to the public outside of FOMC meetings? How do financial markets interpret these news?

When we regress the change in the three-month futures on the change in the one-month futures, we find a coefficient estimate of close to 1; therefore, at a basic level, we can think of slope as a difference in differences: $slope = [\mathbb{E}_{t+1}(r_3) - \mathbb{E}_{t+1}(r_1)] - [\mathbb{E}_t(r_3) - \mathbb{E}_t(r_1)]$. A positive slope factor reflects market expectations of a faster monetary policy tightening, or markets assume that interest rates three months from now, $\mathbb{E}_{t+1}(r_3)$, will be higher relative to what the market expected last week and relative to the change in expectations for the federal funds rate in one month. In Section 2, we motivate the regression and our choice of terminology in a simple factor model.

Empirically, we create the slope factor using end-of-day data from Wednesday of week t to Wednesday of week $t+1$ following (Lo and MacKinlay, 1988). The Wednesday to Wednesday convention is standard in the literature, because it minimizes the number of missing observations. We use slope to predict returns over the following week starting with Wednesday of week $t+1$.[2] The predictability we uncover is economically large and is robust to the inclusion of lagged weekly returns.[3] The predictability is contained in the following week and is a robust finding across subsamples from 1988 (the beginning of the federal fund futures market) to 2007.[4] The weekly predictability is of similar magnitude and is orthogonal to the predictive power of other standard return predictors such as the dividend-price ratio, the VIX, the variance risk premium, or the term spread. We follow Welch and Goyal (2007) and find the predictability holds out-of-sample and beats a naive forecast throughout the sample period contrary to the predictability by the dividend-price ratio which is one of the most successful return predictors in the literature.

The FOMC has eight scheduled meetings per year, and a large literature studies the effects of monetary policy shocks on financial markets in narrow event windows bracketing those eight meetings. Since the first meeting in 1994, the FOMC has released a press statement after meetings and policy decision explaining the decision and discussing the future stance of monetary policy. Our findings are similar in magnitude when we exclude weeks with FOMC meetings and decisions, and does not vary with turning points in monetary policy or policy decisions during unscheduled meetings.

During the same time period, the FOMC changed the conduct of monetary policy and shifted to a more granular, inertial approach. This increased transparency has decreased the size of monetary policy shocks around FOMC meetings over time (see, e.g., Gorodnichenko and Weber, 2016). We find that small values of the slope factor do not drive our findings.

But policymakers also attempt to guide financial markets throughout the year and not only during scheduled meetings. We use linguistic analysis and find that a more hawkish tone in speeches by the chair or vice chair predicts a faster monetary policy tightening. Our findings are consistent with the idea that monetary policy became more transparent in the

[1] We focus on the one- and three-month futures because longer-term futures either did not exist at the beginning of our sample (1994) or were not heavily traded (see discussion in Gürkaynak et al., 2005b). In robustness checks, we also replicate our results with longer-dates futures. In addition, Gertler and Karadi (2015) instrument for monetary policy shocks using different proxies and find that the change in the three-month federal fund futures has the strongest explanatory power.

[2] Equity markets close after the close of futures markets and market participants could trade on the predictions of the slope factor.

[3] Weekly stock returns are autocorrelated; see Lo and MacKinlay (1988).

[4] The zero lower bounds on nominal interest rates determine the end of our sample period. We use longer-dated futures contracts to construct a slope factor during the zero-lower-bound period and find results consistent with our baseline analysis (see discussion below and in the Online Appendix).

1990s. In fact, repeating the introductory quote, Ben Bernanke states in his blog that "monetary policy is 98% talk and only 2% action."[5]

Ozdagli and Weber (2016) find a larger effect of surprise monetary easing on financial markets than of surprise tightening. We also find a larger forecasting power of slope in periods with negative slope values, that is, when market participants expect faster monetary policy easing.

One channel through which our slope factor might affect stock returns is through changing expectations about changes in future short-term interest rates. The slope factor predicts changes in future federal funds rates over the following two months and forecast revisions of professional forecasters over the next quarter. Macro news explains 9% of the variation in the slope factor but does not drive our return predictability. Hence, news about the economy is unlikely to drive the predictability of weekly stock returns by the slope factor; rather, news about the stance on monetary policy is likely to drive the predictability.

The predictability we uncover is economically large. Using insights from Campbell and Thompson (2008) and Cochrane (1999), we show that an investor conditioning on the slope factor can increase the weekly Sharpe ratio by more than 20% compared to a buy-and-hold investor. We argue below that trading based on the predictions of the slope factor is feasible and transaction costs are small.

Our results are consistent with a delayed market reaction to monetary policy news and short-run monetary policy momentum (Neuhierl and Weber, 2018). Greenwood et al. (2018) develop a model of market segmentation with slow-moving capital across markets in which investors might react with a delay to news in markets others than the one they trade in.

1.1. Related literature

A large literature at the intersection of macroeconomics and finance investigates the effect of monetary policy shocks on asset prices in an event-study framework. In a seminal study, Cook and Hahn (1989) examine the effects of changes in the federal funds rate on bond rates using a daily event window. They show that changes in the federal funds target rate are associated with changes in interest rates in the same direction, with larger effects at the short end of the yield curve. Bernanke and Kuttner (2005)—also using a daily event window—focus on unexpected changes in the federal funds target rate. They find that an unexpected interest rate cut of 25 basis points leads to an increase in the CRSP value-weighted market index of about 1 percentage point. Gürkaynak et al. (2005b) focus on intraday event windows and find effects of similar magnitudes for the S&P500. Lucca and Moench (2015) document that stock returns already appreciate in the 24 h before the actual FOMC announcement. Savor and Wilson (2013) show that 60–80% of the realized equity premium is earned around scheduled macroeconomic news announcements such as the FOMC meetings. Ozdagli and Weber (2016) decompose the overall response into a direct demand effect and higher-order network effects using spatial autoregressions, and find that more than 50% of the overall market response comes from indirect effects. Hanson and Stein (2015) study the effect of monetary policy shocks on future long-term real rates. Fontaine (2016) estimates a dynamic term structure model and finds that uncertainty about future rate changes is cyclical. Leombroni et al. (2018) construct a European monetary policy communication shock and show it affects risk premia.

Besides the effect on the level of the stock market, researchers have recently also studied cross-sectional differences in the response to monetary policy. Ehrmann and Fratzscher (2004) and Ippolito et al. (2018), among others, show that firms with high bank debt, low cash flows, small firms, firms with low credit ratings, low financial constraints, high price-earnings multiples, and Tobin's q show a higher sensitivity to monetary policy shocks, which is in line with bank-lending, balance sheet, and interest rate channels of monetary policy. Gorodnichenko and Weber (2016) show that firms with stickier output prices have more volatile cash flows and high conditional volatility in narrow event windows around FOMC announcements. Weber (2015), Bhamra et al. (2018) and D'Acunto et al. (2018) study how firm-level and portfolio returns vary with measured price stickiness, and show that sticky-price firms have higher systematic risk, lower financial leverage, but are more sensitive to monetary policy shocks.

We also contribute to a long literature on return predictability. Campbell (1991) and Cochrane (1992) start from a first-order Taylor series approximation of the definition of returns, and show that variation in the dividend-price ratio has to predict either future cash flows or expected returns. Empirically, they find that the dividend-price ratio is a strong predictor of stock returns, especially at horizons longer than one year, whereas they do not find any cash-flow predictability. Lettau and Ludvigson (2001) provide evidence for return predictability using a proxy for the consumption-wealth ratio. Evidence for return predictability by the dividend-price ratio has declined in recent years (see, e.g., Welch and Goyal (2007)). Lettau and Van Nieuwerburgh (2008), Cochrane (2008), and Van Binsbergen and Koijen (2010) allow for structural breaks in the process for the dividend-price ratio, impose theoretical predictions, or estimate a latent process and find strong evidence in favor of return predictability. Ang and Bekaert (2007) and Fama and French (1988) show that short-term interest rates, term spreads, and default spreads are strong predictors of aggregate market returns, whereas Kelly and Pruitt (2013) use information in the cross section of book-to-market ratios. Bianchi et al. (2016) show low frequency shifts in the consumption-wealth ratio of Lettau and Ludvigson (2001) and relate it to changes in the long run expected value of the real federal funds rate. They show a consumption-wealth ratio corrected for structural breaks has strong predictive power for future stock returns. All

[5] See: http://www.brookings.edu/blogs/ben-bernanke/posts/2015/03/30-inaugurating-new-blog.

these studies find evidence for return predictability at longer horizons typically longer than a few quarters and up to several years.

A recent literature studies the effect of macro announcements on financial markets. Andersen et al. (2003) construct surprises from Money Market Services and show that the conditional mean of six exchange rate jumps following the announcement surprises. Gürkaynak et al. (2005a) use the same surprise data and find a strong impact of macro surprises on long-term yields. Gilbert (2011) shows that the reaction of the S&P500 to these surprises is consistent with predictions of rational expectations trading models, whereas (Gilbert et al., 2017) show that the intrinsic value of macro surprises drives the financial markets response. Ghosh and Constantinides (2016) show innovations in macroeconomic variables are highly correlated with the dividend-price ratio. We also use data from Money Market Services to study the impact of macro surprises on the slope factor and show that financial forecasters adjust their forecasts for federal funds rates following changes in the slope factor.

We make the following contributions to the literature. First, we document that monetary policy has large effects on asset prices outside of the eight scheduled FOMC meetings. Second, we find that changes in expectations about the future path of short-term interest rates are important for the response of stock returns, providing evidence in favor of the effectiveness of forward guidance outside of liquidity traps. Third, we find that speeches by the chair affect the slope factor, which then predicts future changes in short-term interest rates. But ultimately, the question remains why financial markets react so strongly to macroeconomic surprises in general and monetary policy news in particular. Does monetary policy news predict future consumption growth, do market participants reach for yield, or does monetary policy directly affect risk premia?

2. Data

In this section, we introduce the different data sources, detail the construction of the slope factor, and report descriptive statistics.

2.1. Stock returns

We sample daily returns for the CRSP value-weighted index including dividends directly from CRSP. The index is an average of all common stocks trading on NYSE, Amex, or Nasdaq. We then subtract the risk-free rate to obtain excess returns and compound those from Thursday of week $t+1$ to Wednesday of week $t+2$ in line with Lo and MacKinlay (1988) to minimize the number of missing observations due to exchange closures. If the Wednesday in week $t+2$ is missing, we use Thursday's closing price, and if both Wednesday and Thursday (in week $t+2$) are missing, we use Tuesday's closing price. If Tuesday, Wednesday, and Thursday are missing, we report the return as missing for that particular week.[6]

2.2. Federal funds futures data

Federal funds futures started trading on the Chicago Board of Trade in October 1988. These contracts have a face value of $5,000,000. Prices are quoted as 100 minus the daily average federal funds rate as reported by the Federal Reserve Bank of New York. Federal funds futures face limited counterparty risk due to daily marking to market and collateral requirements by the exchange. We use end-of-day data of the federal funds futures directly from the Chicago Mercantile Exchange (CME). Futures contracts with maturity of up to three years trade on the CME, but futures with maturities longer than six months are not very liquid.[7]

Our sample period starts in 1994 and ends in 2007 for a total of 725 weeks. We start in 1994 to be comparable to the large event-study literature. With the first meeting in 1994, the FOMC started to communicate its decision by issuing press releases after meetings and policy decisions. The liquidity trap and zero lower bound on nominal interest rates determine the end of our sample because there is little variation in federal funds futures-implied rates. In robustness checks, we employ data going back to 1988, when federal funds futures were introduced, and we study changes in longer-term futures during the liquidity trap period for a sample until 2018.

2.3. Slope factor

Most previous papers have studied the relationship between monetary policy surprises and stock returns in an event study around FOMC press releases. Kuttner (2001) shows that scaled changes of the current-month futures allow isolating the surprise component of monetary policy.[8] The FOMC has eight scheduled meetings per year and, starting with the first meeting in 1994, most press releases are issued around 2:15 p.m. E.T.

We instead are interested in whether monetary policy also matters for asset prices outside of narrowly defined event windows and whether changes in expectations for the path of future short-term rates are important drivers of future stock returns.

[6] We lose approximately 0.6% of all observations due to this convention. Most of these observations are around Christmas and New Year.

[7] Gürkaynak et al. (2005b) argue that federal fund futures with maturity beyond three months were illiquid before 1998.

[8] The scaling is necessary because of the settlement terms of the futures contracts; see Kuttner (2001).

Let $ff_{t,1}$ denote the rate implied by the one-month federal funds futures on date t and assume a FOMC meeting takes place during that month. d_1 is the day of the FOMC meeting and m_1 is the number of days in the month. We can then write $ff_{t,1}$ as a weighted average of the prevailing federal funds target rate, r_0, and the expectation of the target rate after the meeting, r_1:

$$ff_{t,1} = \frac{d_1}{m_1} r_0 + \frac{m_1 - d_1}{m_1} \mathbb{E}_t(r_1) + \mu_{t,1}, \tag{1}$$

where $\mu_{t,1}$ is a risk premium.[9] Gürkaynak et al. (2007) estimate risk premia of one to three basis points, and (Piazzesi and Swanson, 2008) show that they only vary at business cycle frequencies. We focus on weekly changes and neglect risk premia in the following as is common in the literature.

The one-week change in the one-month futures implied rate in months with FOMC meetings is:

$$\Delta ff_{t,t+1,1} = \frac{m_1 - d_1}{m_1} [\mathbb{E}_{t+1}(r_1) - r_0)]. \tag{2}$$

When t and $t+1$ are in different months, we already use the next month's future; that is, we roll the contract forward.

Similarly, we can write the one-week change in the three-month futures implied rate in months with FOMC meetings as:

$$\Delta ff_{t,t+1,3} = \frac{d_3}{m_3} \left[\mathbb{E}_{t+1}(r_{3\_}) - \mathbb{E}_t(r_{3\_})\right] + \frac{m_3 - d_3}{m_3} [\mathbb{E}_{t+1}(r_3) - \mathbb{E}_t(r_3)], \tag{3}$$

where $r_{3\_}$ denotes the federal funds target rate prevailing before the FOMC meeting, which in most cases will coincide with r_1.

Changes in the near-term futures contract contain information affecting the level of all future federal funds target rates, whereas changes in the longer-term futures also contain information about the path of future short-term rate changes. We assume

$$\Delta ff_{t,t+1,1} = level_{t,t+1} \tag{4}$$

$$\Delta ff_{t,t+1,3} = \beta level_{t,t+1} + slope_{t,t+1}. \tag{5}$$

We can now define the slope factor as the residual of a regression of weekly changes in the three-month federal funds futures-implied rate, $\Delta ff_{t,t+1,3}$, on a constant and changes in the one-month futures-implied rate:

$$\Delta ff_{t,t+1,3} = \alpha + \beta \Delta ff_{t,t+1,1} + slope_{t,t+1}. \tag{6}$$

The definition of our slope factor is similar in spirit to structural vector autoregressions (VAR), and we identify slope by imposing a zero restriction. Of course, similar to identified VARs, different assumptions are possible.

The point estimate of α is -0.00 and is indistinguishable from 0, and the point estimate of β is 1.17 with a standard deviation of 0.03:

$$\Delta ff_{t,t+1,3} = \underset{(0.00)}{-0.00} + \underset{(0.03)}{1.17} \Delta ff_{t,t+1,1} + slope_{t,t+1}.$$

The R^2 of the regression is 67%, which indicates that the slope factor explains around one third of the variation in three-month futures changes.

Fig. 1 plots the times series of slope in the top panel, together with the time series for changes in the one-month and three-month futures-implied rates in the middle and bottom panel, respectively. By construction, slope is orthogonal to the change in the one-month futures-implied rate but exhibits a correlation of 57% with changes in the three-month futures-implied rate, indicating that the slope factor contains useful information about the path of future monetary policy changes.

Figure A.1 in the Online Appendix plots the regression coefficient of Eq. (6) for a rolling estimating. The red dashed line uses a constant window of 250 weeks, whereas the blue solid line indicates estimates from an expanding window sample. The regression estimate is stable through time and varies between 1.07 and 1.33.

The autocorrelation of the slope factor is 0.11 and spurious predictability arising from highly persistent regressors is no concern in our setting (see Stambaugh, 1999).

In our empirical analysis, we use a regression residual to predict excess returns. Full-sample estimates incorporate forward-looking information, and the estimation of slope requires a correction of standard errors. Economically, the point estimate is close to 1. We exploit this feature and construct as robustness a slope factor as a simple difference in differences: $slope = \Delta(ff_{t+1,3} - ff_{t,3}) - \Delta(ff_{t+1,1} - ff_{t,1})$. This slope has the advantage that we do not use forward-looking information and it does not require any estimation. It also allows a simple interpretation of slope as indicating faster future monetary policy tightening and easing: $slope = \Delta(ff_{t+1,3} - ff_{t+1,1}) - \Delta(ff_{t,3} - ff_{t,1})$. A positive slope factor reflects market expectations of a faster monetary policy tightening, or markets assume that interest rates three months from now will be higher relative to what the market expected last week and relative to the change in expectations for the federal funds rate in one month.

[9] We implicitly assume the beginning of week t is after the previous FOMC meeting. Meetings are typically around six to eight weeks apart.

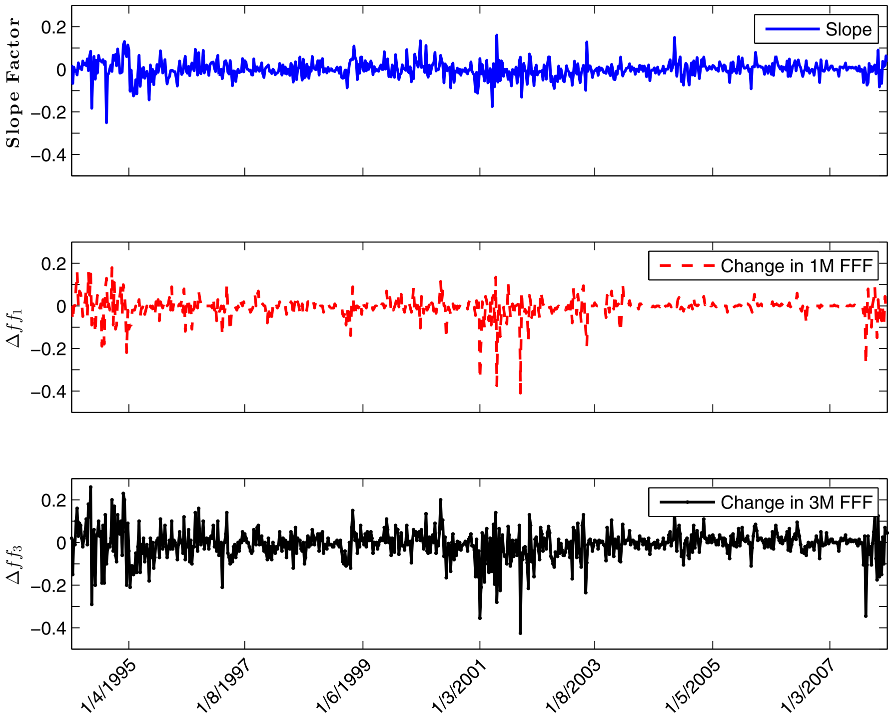

Fig. 1. Time series of slope factor and changes in futures. *This figure plots the time series of the slope factor in the top panel, the weekly changes in the one-month futures-implied federal funds rate in the middle panel, and the weekly changes in the three-month futures-implied federal funds rate in the bottom panel for a sample from 1994 to 2007.*

Table 1
Descriptive statistics. *This table reports descriptive statistics for the slope factor, one- and three-month federal funds futures-implied rates $ff_{t,t+1}$, one-week changes in these rates, the actual federal funds target rate, the absolute value of the slope factor, and weekly excess returns of the CRSP value-weighted index. The sample period is January 1994 to December 2007 for a total of 725 weeks.*

	$Slope_t$	$ff_{t,t+1,1}$	$ff_{t,t+1,3}$	$\Delta ff_{t,t+1,1}$	$\Delta ff_{t,t+1,3}$	Target Rate	abs($Slope_t$)	R_{t+1}
Mean	0.00	4.23	4.29	−0.01	−0.01	4.20	0.03	0.12
Std	(0.04)	(1.73)	(1.74)	(0.05)	(0.07)	(1.75)	(0.03)	(2.21)
Nobs					725			

2.4. Descriptive statistics

Table 1 reports descriptive statistics of weekly changes in the futures-implied rate, the slope factor, and weekly stock returns. The slope is a regression residual and has a mean of 0. The federal funds rate implied by the one- and three-month federal funds futures are 4.23% and 4.29%, respectively, with average weekly changes of −0.01 for both. The average federal funds target rate was 4.20% during our sample period, and the CRSP value-weighted index had an average weekly excess return of 0.12%.

3. Empirical results

3.1. Methodology

We focus on one-week predictability of stock returns by the slope factor to establish an effect from changes in the future path of monetary policy on stock returns. Contemporaneous windows might cause concerns of reverse causality. Stock prices are the present discounted value of future dividends, and the CRSP value-weighted index captures almost 100% of the overall market capitalization in the United States. In the long run, economy-wide dividends and GDP are co-integrated, good news about future dividends is good news about the economy, and market participants might expect a faster tightening of future interest rates following good news. In this case, we would find a positive contemporaneous relationship between our slope

Table 2
Predictive regressions. *This table reports weekly predictive regressions of the excess returns of the CRSP value-weighted index on the slope factor ($Slope_t$), lagged index returns (R_t), the dividend-price ratio (dp_t), the VIX (VIX_t), realized variance (RV_t), the variance risk premium (VRP_t), the federal funds target rate ($Fedfunds_t$), the term spread ($TermSpread_t$), and the monetary policy shock (mp_t) from Gorodnichenko and Weber (2016). We report bootstrapped standard errors in parentheses. We construct the slope factor as a regression residual of weekly changes of the three-month federal funds futures-implied rate on the one-month federal funds futures-implied rate (see (Eq. 6)). Our sample period is from the first week of 1994 to the last week of 2007 for a total of 725 weeks.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.12	0.13	−0.47	−0.02	0.03	0.14	0.03	−0.05	0.12	−1.36*
	(0.08)	(0.09)	(0.36)	(0.29)	(0.20)	(0.15)	(0.22)	(0.20)	(0.09)	(0.71)
$Slope_t$	−7.70***	−6.96***	−6.88***	−6.85***	−6.87***	−6.95***	−6.97***	−6.83***	−6.35***	−5.89***
	(2.07)	(1.98)	(1.99)	(1.97)	(1.97)	(1.99)	(1.99)	(1.99)	(1.96)	(1.96)
R_t		−0.09*	−0.08*	−0.08*	−0.09*	−0.09*	−0.09*	−0.08*	−0.11**	−0.10**
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
dp_t			36.79*							61.21**
			(20.13)							(24.73)
VIX_t				0.01						0.01
				(0.02)						(0.03)
RV_t					0.01					0.01
					(0.02)					(0.03)
VRP_t						0.00				
						(0.03)				
Fed funds$_t$							0.02			−0.09
							(0.05)			(0.10)
Term Spread$_t$								0.07		0.20
								(0.07)		(0.15)
mp_t									−11.76***	−11.51***
									(2.91)	(2.91)
R^2	1.91	2.61	3.04	2.66	2.66	2.62	2.65	2.55	5.56	6.47
Nobs	725	724	724	723	724	723	724	718	724	717

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

factor and stock returns. Rigobon and Sack (2003) use a heteroskedasticity-based identification method and indeed find monetary policy systematically reacting to movements in stock prices.[10]

Another potential concern of studying the contemporaneous relationship between the slope factor and stock returns is the fact that both might react to macroeconomic announcements during the week. Weaker-than-expected unemployment numbers might lead to a drop in stock prices and expectations that the FOMC might lower the speed of interest rate increases. We would find a positive contemporaneous association between slope and stock returns which would, however, be an endogenous response to news about the economy.

Changes in slope could still reflect changes in economic fundamentals. An upward adjustment in inflation expectations or GDP growth could lead to a positive slope factor.[11] We would expect a positive association between slope and future stock returns if slope captures positive news about the macroeconomy, but we find instead slope predicting negative returns. We might expect no reaction of subsequent stock returns to slope if slope captures news of changes in inflation expectations, because stocks are claims to real assets and should be less affected by inflation.[12]

In Section 4.4, we show that speeches by the chair and vice chair, instead, affect the slope factor. Macro news also affects the slope factor, but has no independent predictive power for future stock returns conditional on the slope factors (see Online Appendix). Professional forecasters instead change their forecasts about future federal funds rates as a response to changes in the slope factor (see Section 4.2). Our results are consistent with a delayed market reaction to monetary policy news and short-run monetary policy time series momentum.

3.2. Baseline

Table 2 presents our baseline finding regressing weekly excess returns in percent of the CRSP value-weighted index starting in week $t+1$, R_{t+1}, on the slope factor of week t, $slope_t$, calculated according to Eq. (6) and additional covariates measured at the end of week t, X_t:

$$R_{t+1} = \alpha + \beta slope_t + \gamma' X_t + \varepsilon_t. \tag{7}$$

We use in-sample slope estimates in our baseline specification but show results for the simple-difference slope below. We address the first-stage estimation of the slope factor by reporting bootstrapped standard errors in parentheses. We resample

[10] We also find a positive contemporaneous association of the slope factor and stock returns at the weekly frequency which is, however, fully driven by conventional monetary policy shocks (see discussion in the Online Appendix).

[11] Empirically, a Taylor (1993) rule in which nominal interest rates respond positively to inflation and output growth is a good description of actual nominal rates in the data.

[12] For a discussion, see Katz et al. (2017) but also Fama and Schwert (1977) and Bhamra et al. (2018).

changes in federal funds futures and returns simultaneously. For each sample we draw, we re-estimate the slope factor and then estimate the predictive regression (on the re-sampled data). We repeat this process 1000 times to obtain standard errors for the regression coefficients in the predictive regression.[13]

The point estimate of β is negative and highly statistically significant. Economically, a one-standard-deviation increase in the slope factor (0.04) leads to a drop in weekly returns of 0.3%, which is 1.5 times the average weekly return and 13.5% of a one-standard-deviation move in returns (2.19%). The slope factor explains around 2% of the weekly variation in stock returns.

Campbell et al. (1997) document that weekly stock returns are negatively autocorrelated in the modern period. We add the lagged excess return of the CRSP value-weighted index in column (2). We also find negative autocorrelation for our sample period. However, adding the lagged excess return has little influence on our point estimate of β and adds little explanatory power. Interestingly, the lagged return only explains around 1% of the weekly variation in excess returns when it is the only explanatory variable.

The remaining columns of Table 2 study the robustness of the predictive power of the slope factor when we add other, standard return predictors, which are available at sufficiently high frequencies.

The dividend-price ratio predicts variation in risk premia at the business-cycle frequency (see Campbell, 1991; Cochrane, 1992). We add the dividend-price ratio of the CRSP value-weighted index (dp_t) as a return predictor in column (3). We also find that high dp_t predicts high weekly returns but barely changes the point estimate of the slope factor.

Bollerslev et al. (2009) argue that time-varying economic uncertainty affects risk premia, and they provide evidence of predictability of quarterly excess returns by the variance risk premium. We add the level of the VIX index (VIX_t) in column (4), realized variance (RV_t) in column (5), and the variance risk premium (VRP_t) as the difference between VIX_t and RV_t in column (6). We do not find evidence for predictability of weekly stock returns by any of the three variance-related measures, and adding them has little impact on the predictability by the slope factor.

Both stock returns and slope might vary with the level of the federal funds rate. To ensure our baseline regression does not capture these effects, we add the federal funds target rate as covariate in column (7). We find little evidence supporting this consideration. The point estimate is statistically insignificant, the point estimate of β barely changes, and the explanatory power of the regression remains identical.

The slope of the yield curve might be a useful predictor of recessions and economic activity. Fama and French (1988) and Lettau and Ludvigson (2010) document the forecasting power of the term spread for stock returns. We add the term spread from the Federal Reserve Bank of Cleveland in column (8). The term spread has no predictive power for weekly excess returns, and adding it as an additional covariate has little impact on our point estimate of interest.

In column (9), we add the 30-minute monetary policy shock around FOMC announcements from Gorodnichenko and Weber (2016), (mp_t).[14] Tighter monetary policy negatively predicts the next weeks' stock returns but has little impact on the forecasting power of the slope factor.

Column (10) adds all covariates jointly and supports our baseline finding. All predictors jointly explain 7.5% of the weekly variation in stock returns, with the slope factor remaining highly statistically and economically significant. We find in unreported results the explanatory power decreases by 1.5% when we exclude the slope factor from column (10).

Our baseline analysis stops in 2007 because the federal funds target rate subsequently hit the zero lower bound on nominal interest rates. Table A.1 in the Online Appendix report a specification in which we append the sample until the last week of 2018 with a slope factor constructed from changes in six-months fed funds futures implied rates regressed on changes in the implied rates of three-months fed funds futures. Results are consistent with our baseline findings. We also report in Table A.2 in the Online Appendix results for a slope factor constructed using six-months and one-months futures and results are similar.

3.3. Subsample analysis

Stock markets react strongly to monetary policy surprises in tight windows around FOMC press releases (Bernanke and Kuttner, 2005), but an upward drift occurs in stock returns in the 24 h before scheduled FOMC meetings (see Lucca and Moench, 2015). We study in Table 3 whether a systematic response of stock returns to monetary policy surprises around FOMC press releases or an upward drift in stock returns before the release might drive our findings. Column (1) repeats our baseline estimation. Column (2) removes all weeks from our sample that contain a scheduled or unscheduled FOMC meeting during the period over which we measure stock returns. This restriction removes 118 weeks from our sample but has little impact on our point estimates, statistical significance, or explanatory power of the slope factor. Column (3), instead, removes weeks with FOMC meetings during the period over which we estimate the slope factor. Again, we find little evidence for FOMC weeks driving our findings. Lastly, column (4) removes weeks with meetings in either week t or week $t+1$, reducing our sample size by 1/3. The point estimate is now slightly reduced to -6.10 from our baseline estimate of -6.96, but statistical significance and explanatory power are unchanged. Hence, FOMC meetings do not drive our results.

The sensitivity of stock returns to monetary policy shocks varies across types of events. Ozdagli and Weber (2016) find larger sensitivities of stock returns to monetary policy shocks on turning points in monetary policy compared to regular

[13] We do not detect any significant error-term autocorrelation, which is why we do not block bootstrap the data.

[14] We merge the monetary policy shock during the week over which we calculate the slope factor and set it to zero for weeks without a meeting.

Table 3

Predictive regressions: Meeting weeks. *This table reports weekly predictive regressions of the excess returns of the CRSP value-weighted index on the slope factor ($Slope_t$) and lagged index returns (R_t), excluding weeks with scheduled and unscheduled FOMC meetings. We report bootstrapped standard errors in parentheses. We construct the slope factor as a regression residual of weekly changes of the three-month federal funds futures-implied rate on the one-month federal funds futures-implied rate (see (Eq. 6)). Our sample period is from the first week of 1994 to the last week of 2007 for a total of 725 weeks.*

	All weeks (1)	No meeting Return week (2)	No meeting Previous week (3)	No meeting In either week (4)
Constant	0.13	0.23***	0.12	0.24**
	(0.09)	(0.09)	(0.09)	(0.09)
$Slope_t$	−6.96***	−6.87***	−6.58***	−6.10**
	(1.98)	(2.50)	(2.15)	(2.78)
R_t	−0.09*	−0.08	−0.08	−0.09
	(0.05)	(0.06)	(0.06)	(0.07)
R^2	2.61	2.10	2.25	1.74
Nobs	724	606	606	490

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

meetings, and no sensitivity on intermeeting policy decisions. Turning points are target-rate changes in the direction opposite to the previous target-rate change. Turning points signal changes in the current and future stance on monetary policy (Coibion and Gorodnichenko, 2012; Jensen et al., 1996; Piazzesi, 2005). Intermeeting policy decisions are changes in target rates on unscheduled meetings of the FOMC. Faust et al. (2004) argue that intermeeting policy decisions are likely to reflect new information about the state of the economy, and hence, the stock market might react to news about the economy rather than changes in monetary policy.

Table A.3 in the Online Appendix adds dummy variables equal to 1 if the week during which we create the slope factor contains any meeting (*meeting*), a regular meeting (*regular*), an unscheduled meeting (*intermeeting*), and if the policy decision was a turning point (*turningpoint*), as well as interactions with the slope factor. Stock returns are negative following any meetings, weeks of regular FOMC meetings, intermeetings, and weeks in which the decision was a turning point (columns (2) to (5)). However, we do not find any variation of the slope factor as a function of meeting types.

Faster monetary policy easing might have different effects than an expected increase in the speed of tightening. Ozdagli and Weber (2016) show for a sample similar to ours that the stock market reacts mainly to surprise cuts in interest rates. Table A.4 in the Online Appendix conditions the slope factor on positive and negative realizations. We see in columns (1) and (2) that most of the predictive power comes from negative realizations of slope: increases in the speed of monetary policy easing are more than three times as important as positive values of slope. Defining upside and downside slope factors as realizations more than one standard deviation above or below 0 similar to Lettau et al. (2014) leads to similar conclusions (see columns (3) and (4)).

Monetary policy has become more predictable over time, and many slope observations are small in absolute value. To ensure these observations do not drive our results, we follow (Gorodnichenko and Weber, 2016) and restrict our sample to weeks with values of the slope factor larger than 0.015 in absolute value in column (5), cutting our sample almost in half. Economic and statistical significance increases when we exclude small values of the slope factor.

Section II in the Online Appendix contains extensive robustness checks including the simple-difference slope, controlling for principal components for federal funds futures and the target and path of Gürkaynak et al. (2005b) and report results for different subsamples and forecast horizons. Across sample cuts, controls, and variations, we find a robust predictive power of slope and no predictive power beyond the one-week horizon.

3.4. Uncertainty and predictability

Periods of heightened uncertainty tend to be periods when stock return predictability is especially strong (see Cujean and Hasler, 2017). To study whether economic uncertainty is also important for the predictability of the slope factor, we first interact slope with the VIX (Bloom, 2009) in Table 4.[15] We repeat our baseline specification in column (1) for convenience. In column (2) we indeed see that the predictive power of slope is concentrated in times of high uncertainty: The interaction term with VIX is negative and the slope in level loses statistical significance. Columns (3)–(5) introduce interaction terms with dummy variables that equal 1 when the VIX is above the 50th, 75th, and 90th percentile in our sample. In these specifications, we find large and negative estimates for the interaction terms but also negative point estimates for the slope factor in levels. These results suggest that the predictability of the slope factor is highest in times of high economic uncertainty.

[15] We thank Oleksiy Kryvtsov for this excellent suggestion.

Table 4
Predictive regressions: VIX interactions. *This table reports weekly predictive regressions of the excess returns of the CRSP value-weighted index on the slope factor ($Slope_t$), lagged index returns (R_t), the VIX (VIX_t), dummy variables that are 1 when the VIX is larger than certain quantiles of the VIX distribution as well as interaction terms with the slope factor. We report bootstrapped standard errors in parentheses. We construct the slope factor as a regression residual of weekly changes of the three-month federal funds futures-implied rate on the one-month federal funds futures-implied rate (see (Eq. 6)). Our sample period is from the first week of 1994 to the last week of 2007 for a total of 725 weeks.*

	Baseline (1)	VIX_t continuous (2)	$VIX_t > Q50$ (3)	$VIX_t > Q75$ (4)	$VIX_t > Q90$ (5)
Constant	0.13	0.04	0.12	0.14*	0.10
	(0.09)	(0.30)	(0.08)	(0.08)	(0.08)
$Slope_t$	−6.96***	5.34	−3.09*	−4.44**	−5.38***
	(1.98)	(6.54)	(1.71)	(1.82)	(1.75)
R_t	−0.09*	−0.06	−0.07	−0.07	−0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
VIX_t		0.00			
		(0.02)			
$Slope \times VIX_t$		−0.64*			
		(0.39)			
$\mathbb{1}_{VIX>Q}$			−0.01	−0.09	0.23
			(0.16)	(0.24)	(0.47)
$Slope \times \mathbb{1}_{VIX>Q}$			−8.55**	−9.02*	−10.39
			(4.26)	(5.41)	(8.94)
R^2	2.61	3.29	3.16	3.14	3.20
Nobs	724	723	724	724	724

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

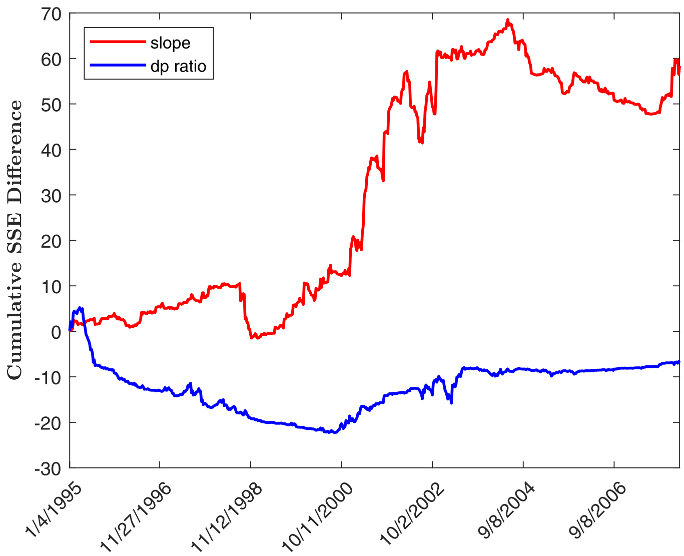

Fig. 2. Weekly out-of-sample predictive performance. *This figure plots the out-of-sample cumulative squared prediction error of a random walk against the predictions of the slope factor in red and the dividend-price ratio (dp ratio) in blue. We construct the slope factor as a regression residual of weekly changes of the three-month federal funds futures-implied rate on the one-month federal funds futures-implied rate (see (Eq. 6)). Our sample period is from the first week of 1994 to the last week of 2007 for a total of 725 weeks.* (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

A different way of studying time variation in the predictability is an out-of-sample forecasting exercise following Welch and Goyal (2007). These authors study the out-of-sample predictive power of popular return predictors and find none of the popular predictors beats the rolling-window mean return. We follow Welch and Goyal (2007) and plot in Fig. 2 the cumulative out-of-sample difference in the squared forecast errors (SSE) for the naive trailing mean forecasts and forecasts by the slope. The top red line plots the SSE for the slope factor and the blue line repeats the exercise for the dividend-price ratio, the most popular return predictor in the asset pricing literature. We see that slope reliably beats the naive sample mean forecast, that is, the cumulative sum (SSE) is positive throughout the sample period, starting already in 1994. The predictability is especially strong starting in 1999 until 2004 and then levels off. The dividend-price ratio, instead, does not outperform the simple mean forecast and results in a negative SSE during the whole sample period.

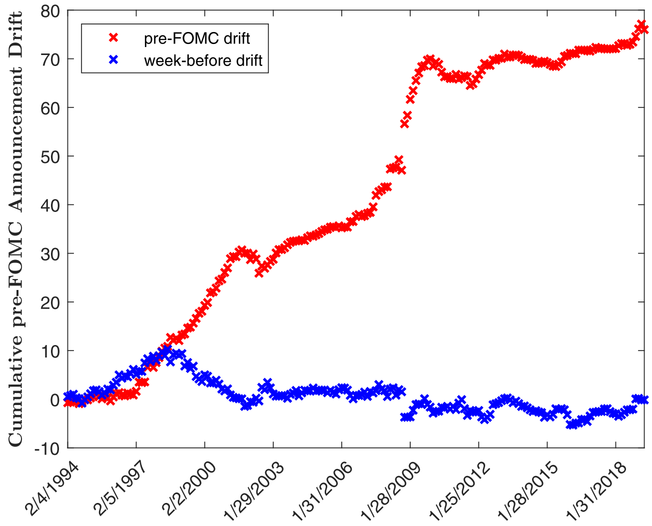

Fig. 3. Cumulative pre-FOMC announcement drift. *This figure plots the cumulative return of the pre-FOMC announcement drift of Lucca and Moench (2015) in red for all regular 203 FOMC meetings from 1994 until May 2019. We use the return of the SPDR S&P500 ETF from 2 pm of the day prior to the meeting until 2 pm of the day of the meeting. We also plot the cumulative return of all 24 h windows 5 trading days before all scheduled FOMC meetings in blue.* (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The results so far suggest that the slope factor is a reliable return predictor and has especially strong predictive power in times of high uncertainty. To better understand whether uncertainty matters more generally for the monetary policy–stock return nexus, we revisit the pre-FOMC announcement drift of Lucca and Moench (2015). These authors show large parts of the realized equity premium in a sample starting in 1994 is earned in the 24 h before FOMC decisions. Fig. 3 replicates their finding plotting the cumulative return of all 24 h windows before all 203 scheduled FOMC meeting for a sample starting in 1994. We use the SPDR S&P500 ETF tick data from NYSE taq to construct the returns in the 24 h before FOMC meetings following Gorodnichenko and Weber (2016). We find returns for the pre-FOMC announcement drift are large and positive for a sample from 1997 until 2002 and then again for a sample from 2007 until 2009 before the announcement drift levels off until the end of the sample in 2019. To show the striking return drift in the 24 h before scheduled FOMC meetings relative to other 24 h windows, we also plot in blue the cumulative return of the 203 24 h windows 5 trading days before the scheduled FOMC meeting as a placebo test following Gorodnichenko and Weber (2016).

The results in this subsection suggest economic uncertainty is an important determinant for the monetary policy–stock market nexus and more research is needed to fully understand the interplay.

4. Economic mechanism and magnitudes

4.1. Future changes

We argue that changes in the whole future path of short-term interest rates matter for changes in asset prices and create a slope factor using changes of federal fund futures of different horizons. We indeed find that slope can predict stock returns: increases in slope result in lower future stock returns. However, we have not shown that changes in the slope factor are related to future changes in federal funds rates.

Table 5 regresses future changes in target rates on the slope factor. We define the one-month change in the target rate as the difference in the actual federal funds target rate over the 21-trading-day period after the period over which we calculate the slope factor. We define longer-period changes accordingly. We see in column (1) that slope predicts one-month changes in federal funds target rates with a positive sign. In column (2), we predict two-month changes in federal funds rates orthogonal to the one-month change. The slope factor predicts two-month changes with a positive sign and adds predictive power to the one-month change. In the remaining columns, we regress future changes of up to six months orthogonalized to the one-month change. We do not detect any predictability in these changes once we condition on the two-month change.[16]

4.2. Changes in expectations

The slope factor has predictive power for future equity returns but also predicts changes in future federal funds rates, whereas speeches by the FOMC chair affects the slope factor as we show below. One interpretation of these results is that

[16] Recall we only use futures of up to three months to create the slope factor.

Table 5
Predictive regressions: Future fed funds rate. *This table reports weekly predictive regressions of changes in future realized federal funds target rates on the slope factor ($Slope_t$), and one-month and two-month changes in federal funds rates ($\Delta M1$, $\Delta M2$) for horizons lasting from one month ($M1$) to six months ($M6$). We report bootstrapped standard errors in parentheses. We construct the slope factor as a regression residual of weekly changes of the three-month federal funds futures-implied rate on the one-month federal funds futures-implied rate (see (Eq. 6)). Our sample period is from the first week of 1994 to the last week of 2007 for a total of 725 weeks.*

	$\Delta M1$ (1)	$\Delta M2 \perp \Delta M1$ (2)	$\Delta M3 \perp \Delta M1$ (3)	$\Delta M4 \perp \Delta M1$ (4)	$\Delta M5 \perp \Delta M1$ (5)	$\Delta M6 \perp \Delta M1$ (6)
Constant	0.00	0.01*	0.03***	0.04***	0.05***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
$Slope_t$	0.78***	0.98***	−0.13	0.02	0.23	0.29
	(0.23)	(0.21)	(0.30)	(0.35)	(0.45)	(0.63)
$\Delta M1$		0.36***				
		(0.05)				
$\Delta M2$			0.87***	1.20***	1.49***	1.73***
			(0.03)	(0.05)	(0.06)	(0.07)
R^2	2.42	15.35	63.41	63.34	61.00	56.80
Nobs	726	726	726	726	726	726

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6
Predictive regressions: Future forecast changes. *This table reports monthly predictive regressions of changes in expectations of future fed funds rates on the cumulative slope factor over the previous three weeks ($Slope_{t-3:t}$), and the one-month change in expectations for horizons lasting from one quarter ($Q1$) to three quarters ($Q3$). We report Newey–West standard errors in parentheses. We construct the slope factor as a regression residual of weekly changes of the three-month federal funds futures-implied rate on the one-month federal funds futures-implied rate (see (Eq. 6)). Our sample period is from February 1994 to December of 2007 for a total of 163 months.*

	$\Delta Q1$ (1)	$\Delta Q2$ (2)	$\Delta Q3$ (3)	$\Delta Q2$ (4)	$\Delta Q3$ (5)
Constant	−0.01	−0.01	−0.02	−0.00	−0.01
	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
$Slope_{t-3:t}$	0.89***	1.02***	1.00***	0.11	0.12
	(0.17)	(0.16)	(0.16)	(0.08)	(0.12)
$\Delta Q1$				1.03***	1.00***
				(0.04)	(0.04)
R^2	11.32	12.22	11.55	88.26	82.26
Nobs	163	163	163	163	163

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

members of the FOMC communicate news about their monetary policy stance throughout the year outside of scheduled FOMC meetings through speeches and testimonies. If the slope factor reveals news about the future monetary policy stance to the public, we should see market participants updating their expectations for future federal funds rates.

To test for this channel, we regress changes in consensus expectations for future federal funds rates on the slope factor in Table 6. We obtain monthly forecasts for the federal funds rate one to three quarters ahead from Blue Chip financial forecasts. Blue Chip surveys leading business and financial economists typically in a period between the 22nd and 25th of the previous months, and releases the forecasts on the first of the month. We create one-month changes in these forecasts and regress them on the three-week cumulative slope factor ending on or before the 20th of the previous month.[17]

We see in columns (1)–(3) that the three-week slope factor significantly predicts forecast revisions of professional forecasters for future federal funds rates over the next three quarters and explains around 12% of the variation. The coefficient on the slope factor is indistinguishable from 1. Slope loses its forecasting power more than one quarter ahead, once we condition on the forecast revision for the first quarter (see columns (4) and (5)), which we would expect because the slope factor only contains information for future federal funds target rates of up to three months ahead. The one-quarter-ahead forecast revision explains more than 80% of the changes in two- and three-quarters-ahead predictions, indicating high persistence in forecast revisions.

[17] The timing ensures Blue Chip collected the forecasts after the period over which we calculate the slope factor.

Financial market participants update forecasts for future federal funds rates following changes in slope. This finding is consistent with the idea that changes in slope reveal information about the speed of future monetary policy tightening and loosening, and professional forecasters update their forecast to the new information.

4.3. Narrative evidence: Speeches, speed, and momentum

A positive slope factor predicts negative stock returns over the next week. We also find that macro news has little impact on the predictability (see Online Appendix), but market participants instead update their expectations about future federal funds rates. These findings are consistent with delayed market reaction to the monetary policy news, that is, short-run monetary policy momentum, and provide evidence that monetary policy news comes out throughout the year and not only during scheduled FOMC meetings. The FOMC has increased the transparency of their decisions and manages expectations of participants in financial markets in speeches and testimonies. One way the FOMC might affect market expectations about the speed of future monetary policy easing and tightening might be through the tone of speeches, which the slope factor possibly captures. We now discuss as representative example the narrative background for a week in which the slope factor was large in absolute value (above the 95th percentile).

On September 26, 2005, Chairman Alan Greenspan gave a speech to the American Bankers Association Annual Convention in Palm Dessert. He started off with,

> In my remarks today, I plan, in addition, to focus on one of the key factors driving the U.S. economy in recent years: the sharp rise in housing valuations and the associated buildup in mortgage debt. Over the past decade, the market value of the stock of owner-occupied homes has risen annually by approximately 9% on average, from $8 trillion at the end of 1995 to $18 trillion at the end of June of this year. Home mortgage debt linked to these structures has risen at a somewhat faster rate.

The *Washington Post* article, "Concerns Raised as Home Sales, Prices Rise Again; Greenspan Issues Sternest Warning Yet to Bankers Group," says,

> U.S. home sales and prices surged again last month, an industry group reported yesterday, as Federal Reserve Chairman Alan Greenspan warned that the growing use of riskier new mortgages could result in 'significant losses' for lenders and borrowers if the market cools. And some cooling is likely, Greenspan suggested in remarks delivered via satellite to the American Bankers Association convention in Palm Desert, Calif., repeating his view that 'home prices seem to have risen to unsustainable levels' in certain local markets. [...] The Fed [...] indicated it will keep moving the rate higher in coming months to keep inflation under control.

The slope factor is 0.08 in the week ending on September 28, 2005, and the following week's excess return is −1.50%.

4.4. Policy speeches: Linguistic analysis

The example in the previous section is suggestive, but by no means conclusive. We now systematically study whether the tone of speeches correlates with the slope factor. We collect all speeches for members of the FOMC from http://www.federalreserve.gov/newsevents/. To classify the tone of speeches, we use a "search-and-count" approach as in Apel and Grimaldi (2012). Search-and-count is an automated method to classify text into categories. A pre-specified word list which classifies speeches as "hawkish" or "dovish" is the central input. Using this word list, we can count the hawkish and dovish terms within one speech and aggregate over the document. Following this procedure, we obtain a classification if a speech is on average more hawkish or dovish.[18]

As in Apel and Grimaldi (2012), we also compute a net index, to determine if a speech is on average more hawkish, dovish, or possibly neutral. We calculate the net index by

$$NetIndex = \left[\left(\frac{\#hawk}{\#hawk + \#dove}\right) - \left(\frac{\#dove}{\#hawk + \#dove}\right)\right] + 1.$$

A value above 1 implies the speech contains more hawkish than dovish terms, and we would expect a faster future monetary policy tightening; that is, a positive coefficient when we regress the slope on the net index.

We test in Table 7 whether the tone of speeches by FOMC officials affects the slope factor. We see in columns (1) and (2) that more hawkish speeches by any member of the FOMC result in an increase in the slope factor, independent of whether we use the net index or the number of hawkish and dovish terms. Neither the coefficient on the net index nor the coefficient on the components is statistically significant, however.

The media and market participants might not focus on all speeches by all FOMC members equally, and not every FOMC member might convey equally important information on the stance of future monetary policy. At the same time, some FOMC members might be more powerful and able to affect the future path of actual federal funds target rates. In columns (3) and (4), we only study speeches by the chair and vice chair. We see that a more hawkish tone as indicated by the net

[18] The Online Appendix contains more details on the procedure, the actual classification we use in Table A.13, and links to the speeches in Table A.14.

Table 7
Linguistic analysis speeches. *This table reports weekly predictive regressions of the slope factor on speeches by members of the FOMC. We use linguistic analysis to count the number of occurrences of hawkish or dovish words. The Online Appendix contains our dictionary. Hawk – Dove Index is a net index that is larger than 1 if the speech contains more hawkish than dovish terms. Hawk and Dove count the occurrences of hawkish and dovish words. Chair is a dummy that equals 1 if a speech is by the chair or vice chair. We report Newey–West standard errors in parentheses. We construct the slope factor as a regression residual of weekly changes of the three-month federal funds futures-implied rate on the one-month federal funds futures-implied rate (see (Eq. 6)). Our sample period is from the first week of June 1996 to the last week of 2007 for a total of 380 weeks.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	−0.32	−0.13	−1.56***	−0.68**	−1.99*	−0.94	−0.18
	(0.41)	(0.24)	(0.59)	(0.27)	(1.10)	(0.90)	(0.23)
Hawk-Dove Index	0.33		1.06**		1.73**		
	(0.33)		(0.45)		(0.75)		
Hawk		0.09		0.56***		0.61*	0.02
		(0.05)		(0.21)		(0.31)	(0.07)
Dove		−0.09		−0.30*		−0.28*	0.29
		(0.16)		(0.17)		(0.17)	(0.25)
Hawk × Chair							0.43*
							(0.22)
Dove × Chair							−0.68**
							(0.33)
R^2	0.21	0.61	2.98	4.60	12.38	12.35	1.97
Nobs	380	380	173	173	43	43	380
Only Speeches by Chair			X	X	X	X	
At least 1 classification					X	X	

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

index is positively correlated with the slope factor. When we split the net index, we see that a more frequent mentioning of hawkish words by the chair signals faster monetary tightening, whereas a more dovish speech is negatively correlated with the slope factor. We see similar results in columns (5) and (6) when we restrict our sample to speeches by the chair or vice chair that contain at least one of the hawkish or dovish terms of our classification. Speeches now explain more than 12% of the variation in the slope factor, which is a regression residual. In column (7), we interact the hawk and dove classification with a dummy variable which equals 1 when the speech is by the chair or vice chair and results are similar.

In line with the interpretation that speeches are a major driver of the variation in the slope factor, we find only four speeches during the blackout period that have at least one hawkish or dovish classification. The slope factor is economically small in absolute value in all four weeks and well within one standard deviation of 0.

The results on the effect of speeches on the slope factor, the slope factor predicting future interest-rate changes, and the fact that market participants update their forecasts for future federal funds rates, combined, suggest monetary policy predictability and short-run monetary policy momentum.

In Section VII G. of the Online Appendix, we also show the reaction of stock returns to the slope factor does not constitute a reaction to news about the macro economy but rather a reaction to news about the future path of monetary policy.

4.5. Economic magnitudes

We employ the results in Campbell and Thompson (2008) to assess the economic significance of our findings. Specifically, we assess how much an investor could possibly gain following the predictions the slope factor generates, to create a link between statistical measures of forecast performance (out-of-sample R^2) and more interesting economic quantities, such as gains in excess returns or increases in Sharpe ratios. The Online Appendix contains details of the calculations.

We find that an investor with mean-variance preferences and unit risk aversion can increase the average weekly excess returns to 0.81% when trading on the predictions of the slope factor relative to a weekly excess return of 0.53% a buy-and-hold investor earns.

Cochrane (1999) suggests an alternative methodology to evaluate the economic significance of return predictability. When we follow the method in Cochrane (1999), we get an increase in the weekly Sharpe ratio of almost 20% from 7.31% to 9.00% when trading on slope.

Slope is a regression residual and one concern is that trading based on information about the speed of future monetary policy tightening and loosening might not be profitable due to transaction costs (Freyberger et al., 2019). The average percentage bid-ask spread of the SPDR S&P 500 (SPY) between 2002 and 2015 is 0.01% and the median spread is 0.008%. The average absolute weekly excess return instead is 1.7%, indicating transaction costs are not a major concern.

5. Concluding remarks

Stock prices are the present discounted value of future cash flows and should be sensitive to changes in market expectations about the whole path of future short-term interest rates. We construct a slope factor from changes in federal funds futures-implied rates of different maturities to test for this prediction. Increases in the slope factor predict future increases in federal funds target rates and negative stock returns at the weekly frequency. The stock return predictability is a robust feature of the data, holds out-of-sample and during subsamples, and has predictive power similar to or larger than standard return predictors.

The predictive power of the slope factor is large in economic terms. An investor who conditions on the slope factor when making portfolio decisions can increase his weekly Sharpe ratio by 20% compared to a buy-and-hold investor.

Consistent with the idea that "monetary policy is 98% talk and only 2% action,"[19] we find that speeches by the chair and vice chair change the slope factor, which predicts future changes in federal funds target rates as well as forecast revisions by professional forecasters. Our findings indicate that monetary policy affects the real economy and financial markets continuously throughout the year, rather than only during eight scheduled FOMC meetings that have been the focus of an extensive event-study literature.

Speeches affect stock returns via their effect on market participants' expectations about the speed of future monetary policy loosening or tightening. Our findings provide evidence for the power of forward guidance and committing to future interest rate policies outside of liquidity-trap periods.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2019.08.005.

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[19] See: http://www.brookings.edu/blogs/ben-bernanke/posts/2015/03/30-inaugurating-new-blog.

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