Journal of Banking and Finance 128 (2021) 106163

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Asset pricing and FOMC press conferences[☆]

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ARTICLE INFO

Article history:
Received 29 March 2020
Accepted 23 April 2021
Available online 30 April 2021

JEL classification:
G12
G14
E52
E58

Keywords:
Asset pricing
FOMC press conferences
Monetary policy
Risk premia

ABSTRACT

A press conference (PC) organized by the Federal Open Market Committee (FOMC) followed half of the scheduled announcements from 2011 to 2018. We document that excess stock returns are strongly and positively related to their betas on announcement days with a PC. In addition, the cross-sectional dispersion in betas declines substantially on PC days when measured using both daily and intraday return data. These effects are absent on announcement days without a PC. Last, we find that stock-bond correlations are positive (negative) on PC (all other) days and that their variations are related to uncertainty and yield curve information. We discuss implications and possible explanations for our findings.

1. Introduction

Monetary policy decisions exert a considerable influence on asset prices (Bernanke and Kuttner, 2005), and investors require substantial compensation for bearing risk associated with scheduled Federal Open Market Committee (FOMC) announcements (Savor and Wilson, 2013; Lucca and Moench, 2015; Cieslak et al., 2019; Brusa et al., 2020). The FOMC and its members are responsible for the monetary policy of the U.S. Federal Reserve System (Fed) and regularly convene at scheduled meetings to discuss the state of the economy and to make monetary policy decisions. The FOMC started announcing their decisions using press statements in February 1994 and has, in addition, held a press conference (PC) with the Chair of the Board of Governors following half of its meetings from April 2011 to December 2018.[1] Boguth et al. (2019) provide first evidence that stock market returns are higher on PC days and that investors pay more attention and respond more strongly to announcements on these days.[2]

In this paper, we study the broader asset pricing implications of having a PC after every other meeting from 2011 to 2018. We begin our empirical analysis by examining how the Security Market Line (SML) responds to scheduled FOMC announcements with and without a PC. An upward sloping SML is a central prediction of the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966). It represents a necessary, but not sufficient, condition for the CAPM to hold. Our first empirical finding is that excess stock returns are higher and increasing in their betas on scheduled FOMC announcement days with a PC (PC days), but low and unrelated to their betas on announcement days without a PC (non–PC days) and non-announcement days. To estimate the slope

☆ We are grateful to two anonymous referees, Geert Bekaert (the editor), Mikkel M. Bennedsen, Charlotte Christiansen, Tom Engsted, Svatopluk Kapounek (discussant), Einar C. Kjenstad, Stig V. Møller, Bradley S. Paye, Thomas Q. Pedersen, Maik Schmeling, and Andreas Schrimpf as well as seminar participants at Aarhus University and CREATES, the 2019 Nordic Econometric Meeting (NEM) in Stockholm, the 2019 Quantitative Finance and Financial Econometrics (QFFE) conference in Marseille, and the 2019 INFINITI conference in Glasgow for many helpful comments and suggestions. Jonas N. Eriksen acknowledges support from the Danish Council of Independent Research (DFF 7024–00020B). This paper was previously circulated as "Standing at attention: The impact of FOMC press conferences on asset prices".

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[1] Prior to 1994 it was left to market participants to infer the Fed's monetary decisions from their open market operations. The motivation for introducing PCs was to "provide additional transparency and accountability" (Bernanke, 2011). The Chairman of the Federal Reserve, Jerome Powell, announced on June 13, 2018 that the Fed will start to hold a PC following all meetings in 2019 (Cox, 2018).

[2] PCs are held by other central banks as well. Examples include the European Central Bank, The Bank of England (after inflation reports), The Bank of Canada, The Reserve Bank of New Zealand, and the Swiss National Bank. However, only Canada and New Zealand have a PC policy similar to that of the FOMC, whereas the ECB holds PCs after all monetary policy meetings.

https://doi.org/10.1016/j.jbankfin.2021.106163

of the SML, we first construct ten equally sized beta-sorted portfolios by ranking and sorting individual stocks according to their CAPM betas. We then examine the relation between portfolio betas and excess returns separately for non-announcement days, non–PC days, and PC days, respectively, using the classic two-step approach of Fama and MacBeth (1973). Portfolio betas are computed using (i) all available observations and (ii) using day-specific return data to gauge the impact of time variations in portfolio betas on the slope of the SML. We find a strong, positive, and significant relation between average excess returns and portfolio betas as predicted by the CAPM on PC days. An increase in beta of one is associated with an increase in average excess returns of about 34bps (t-stat of 2.63) using full sample portfolio betas and with an increase of 79bps (t-stat of 2.81) using day-specific portfolio betas. Excess returns are well explained by the CAPM on PC days, where we observe a cross-sectional R^2 as high as 83% (87%) with constant (day-specific) betas. A joint test for the cross-sectional pricing errors being zero, however, rejects the CAPM on PC days despite the improved performance. We note that the finding of a positive and sizable SML slope on PC days is consistent with the high PC day excess market return documented in Boguth et al. (2019), the interpretation that beta is an important measure of systematic risk when investors expect to learn about the economy (Savor and Wilson, 2014), and that PCs carry important information for investors (Boguth et al., 2019; Cieslak and Schrimpf, 2019). The slope of the SML is small and statistically indistinguishable from zero on all other days, including non–PC days. We arrive at similar conclusions when augmenting the cross-section with portfolios sorted on idiosyncratic volatility (IVOL) (Ang et al., 2006; 2009) and size and book-to-market equity ratios (Fama and French, 1992), using equal-weighted portfolio returns, and for rolling-window portfolio betas. In all cases, we find a strong and positive relation between portfolio betas and excess returns on PC days.

As the number of non-announcement days and non–PC days far exceeds the number of PC days, our overall results are consistent with the well known and widely-held belief that the empirical SML is too flat (Black, 1972; Black et al., 1972; Frazzini and Pedersen, 2014). The literature offers several explanations for this phenomenon, including borrowing constraints (Frazzini and Pedersen, 2014; Asness et al., 2020), margin requirements (Jylhä, 2018), speculative overpricing (Hong and Sraer, 2016), lottery characteristics (Barberis and Huang, 2008; Bali et al., 2017), and compensation for co-skewness risk (Schneider et al., 2020). Most closely related to our work, Savor and Wilson (2014) provide evidence of an upward sloping SML on days with macroeconomic announcements, including FOMC announcements, over the 1964–2011 period.[3] Our analysis extends the results of Savor and Wilson (2014) by considering the more recent 2011–2018 period, where the Fed has introduced a PC after some, but not all, of its scheduled meetings. We contribute to the literature by distinguishing between PC days and non–PC days, and by showing that this distinction is critical to fully capture the response of the SML to monetary policy announcements. All combined, our results suggest that asset prices behave differently on PC days and non–PC days.

The finding that excess stock returns are larger on PC days compared to all other days could in principle be explained by dynamic risk models (Patton and Verardo, 2012; Savor and Wilson, 2016) if portfolio betas are higher on PC days. While prior studies conclude that portfolio betas are invariant across announcement days (Savor and Wilson, 2014; Wachter and Zhu, 2021), we provide new empirical evidence that portfolio betas change significantly on PC days using both daily and intraday return data. We find that the cross-sectional dispersion in portfolio betas declines substantially on PC days as betas compress towards one. The lower dispersion of betas steepens the slope of the SML on PC days and provides further evidence that the SML responds differently on PC days and non–PC days. Andersen et al. (2020) show that the cross-sectional dispersion in betas generally declines during the trading day using intraday return data and that the decline is stronger on FOMC announcement days. We add to this finding by documenting that the reduction in the cross-sectional beta dispersion is substantially more pronounced on PC days compared to all other days. Studying the evolution of the cross-sectional dispersion in betas over a window around the FOMC announcement from 15 min prior to the announcement to 60 min after the announcement reveals that the strength of the compression is related to stock market uncertainty, economic policy uncertainty, and the level of interest rates.

The observation that the cross-sectional dispersion in portfolio betas declines together with the result that all portfolios enjoy larger excess returns on PC days is hard to reconcile within a standard asset pricing framework as the joint occurrences of (i) higher returns and lower betas and (ii) higher returns and higher betas require different explanations. Hence, our results on the lower dispersion in portfolio betas represents a puzzle. The compression of betas on PC days further provides a challenge to existing models of the announcement day premium that assume invariant portfolio betas (Wachter and Zhu, 2021). The reduction in the cross-sectional beta dispersion itself, however, is consistent with information flows being different on PC days compared to other days (Andrei et al., 2020; Andersen et al., 2020). To corroborate this view, we show that a broad range of commonly employed uncertainty proxies decline significantly on PC days, but remain elevated on non–PC days.

Next, we turn our attention to the U.S. Treasury bond market. Consistent with Lucca and Moench (2015), excess bond returns are not significantly different across non-announcement days, non–PC days, and PC days. The dynamics of bond betas and stock-bond correlations, however, differ markedly across the types of days. Bond betas and stock-bond correlations are negative on non-announcement and non–PC days, which is consistent with the belief that investors have viewed bonds as hedge assets since the late 1990s (Campbell et al., 2017; Kozak, 2019; Campbell et al., 2020). Similarly, Cieslak and Pang (2020) offer a recent explanation for the puzzle that stocks, but not bonds, earn high returns on FOMC announcement days by decomposing the overall stock and bond price response into components related to monetary news, growth news, and two distinct shocks generating time-varying risk premiums: a common risk premium and a hedging risk premium. In their setup, it is possible to explain the negative stock-bond correlations from an increasing importance of the hedging premium shock that has taken place since the late 1990s. This increase can explain the shift from positive to negative stock-bond correlations because the hedging premium component drives stock and bond returns in opposite directions. On PC days, however, bond betas and stock-bond correlations increase substantially and turn positive. We find that stock-bond correlations are associated with stock and bond market uncertainty and the first two principal components (level and slope) of the cross-section of zero-coupon yields estimated using the Gürkaynak et al. (2007) data. Importantly, these variables can account for differences in maturity-specific responses in stock-bond correlation across PC days and non–PC days.

Last, we corroborate our findings in an international setting using a sample of liquid currencies. The Fed enjoys a unique position in the global financial system (Rey, 2013; Miranda-Agrippino and Rey, 2020), and its actions are likely to influence international mar-

[3] Using a similar methodology, Tinic and West (1984) find evidence for the CAPM in January, Hendershott et al. (2020) find evidence for the CAPM during the night, but not during the day, and Ben-Rephael et al. (2021) find evidence for the CAPM in periods with high information consumption. Hasler and Martineau (2020) argue that the CAPM holds period-by-period if investors can hedge risk at no cost.

kets (Brusa et al., 2020).[4] Mueller et al. (2017) show that a strategy that holds foreign currency (and is short the U.S. dollar (USD)) earns large excess returns on FOMC announcement days and that the excess returns are higher for currencies with higher interest rate differentials. Similarly, Avdjiev et al. (2019) show that the dollar has become an important barometer of risk-taking capacity in global capital markets, and Karnaukh (2020) shows that the dollar rises prior to FOMC meetings with a rate hike. We build three carry portfolios (Lustig et al., 2011) using nine developed market currencies relative to the USD and find that carry trade excess returns are significantly larger and increasing in market betas on PC days, and that the effect is stronger for high interest rate countries. This effect reverses on non–PC days, where funding currencies outperform investment currencies. In sum, we show that the introduction of PCs after some, but not all, scheduled FOMC meetings has broad and previously undocumented implications for the behavior of asset prices.

Our work relates to a voluminous literature that studies the effect of monetary policy on asset prices (Shiller et al., 1983; Bernanke and Kuttner, 2005) and the announcement day returns discussed above. Adrian and Liang (2018) provide a recent survey of the literature on monetary policy and risk premia. As we study the impact of introducing PCs following some, but not all meetings, our paper is also related to a literature on central bank communication (surveyed by Blinder et al. (2008)). Gürkaynak et al. (2005) show that monetary policy actions and accompanying statements by the Federal Reserve have important, but distinct, effects on asset prices. Kroencke et al. (2021) add a risk shift surprise that is orthogonal to risk-free interest rate surprises. Rosa (2011, 2016) studies market reactions to different types of central bank communications. Smales and Apergis (2017) examine the complexity of the monetary policy statement language and Ehrmann and Talmi (2020) consider the semantic similarity of monetary policy statements and their impact on market liquidity and volatility, respectively. Cieslak and Schrimpf (2019) show that markets react differently to communication about the economic outlook and the monetary policy stance. Leombroni et al. (2020) investigate the impact of communication shocks on the yield curve, and Schmeling and Wagner (2019) study the link between central bank tone and asset returns.

The rest of the paper unfolds as follows. Section 2 describes the data and their sources. Section 3 presents our main empirical findings for stocks. Section 4 explores empirical results from bond and currency markets. Section 5 discusses implications and possible explanations. Finally, Section 6 provides concluding remarks.

2. Data

This section introduces the data and describes their sources and constructions. We then discuss the choice of sample period based on the Fed's communication policy.

2.1. Data sources

We collect data from several sources. Individual U.S. stock return data are obtained from the Center for Research in Security Prices (CRSP) daily stock file. The sample consists of all common stocks (SHRCD 10 and 11) available from the CRSP tape. We exclude penny stocks with a share price below $5 (Hong and Sraer, 2016). Our main stock market proxy is the CRSP NYSE, AMEX, and NASDAQ value-weighted index of all listed shares. We obtain returns for 25 size- and book-to-market-equity-sorted portfolios from Kenneth French's data library together with one-month U.S. Treasury bill rates.[5] Excess returns are computed with respect to this Treasury bill rate. We collect intraday stock price data from the New York Stock Exchange Trade and Quote (TAQ) database. Treasury bond returns are obtained from CRSP's Daily Treasury Fixed Term Indexes file. Last, daily spot and one-month forward exchange rate data are sourced from Barclays and Reuters via Datastream.

2.2. Portfolio construction

We construct portfolios sorted on betas and IVOL following the existing literature. Specifically, we form ten equally sized beta-sorted portfolios by ranking and sorting individual stocks according to their betas, which we estimate by regressing a stock's daily excess return over the past year on contemporaneous excess stock market returns. We construct ten equally sized IVOL-sorted portfolios analogously by ranking and sorting individual stocks according to their IVOL. We estimate IVOL as the standard deviation of the residual from regressing a stock's daily excess return over the past year on contemporaneous excess stock market returns.[6] Portfolios are re-balanced on the last trading day of every month. We focus on value-weighted returns in our main specifications, but confirm our primary conclusions using equal-weighted returns in the Internet Appendix.

2.3. FOMC announcements and press conferences

We obtain the dates of scheduled FOMC announcements directly from the Federal Reserve.[7] Our main sample includes all scheduled FOMC announcements from the first meeting with a PC in April 2011 to June 2018, where Fed Chairman Jerome Powell announced that the Fed will hold PCs after all meetings from 2019 onwards (Boguth et al., 2019; Cox, 2018). This period contains 58 scheduled announcements of which 30 were followed by a PC and 28 were not. We exclude surprise announcements following unscheduled meetings from our sample. The scheduling of the PCs takes place at least six months in advance and is, like the scheduling of the meetings themselves, independent of macroeconomic developments and market conditions. PCs last on average one hour and consist of an opening statement by the Chair of the Board of Governors followed by a Q&A session with financial journalists. While PCs followed every other meeting from June 2012 onwards, there were some initial irregularities in the scheduling during the first nine meetings.[8] Importantly, these irregularities do not affect our study as all PC dates were known well in advance. The release time of the statements varied between 12:30pm Eastern Time (ET) and 2:15pm during our sample period, and the time of the PC has varied between 2:15pm and 2:30pm. In particular, of the 58 announcements, eight were released at 12:30pm, 43 were released at 2:00pm, and seven were released at 2:15pm. With respect to the timing of PCs, eight PCs took place at 2:15pm and the remaining 22 began at 2:30pm.

[4] Bekaert et al. (2021) argue that the role of U.S. monetary policy has been exaggerated and instead provide empirical evidence for non-monetary, policy-driven risk and uncertainty spillovers, respectively, across countries that originate from more countries than simply the U.S.

[5] Kenneth French's data are accessible at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[6] We obtain qualitatively identical results if we instead define IVOL as the standard deviation of the residual from the Fama and French (1993) three-factor model.

[7] Historical meeting calendars, statements, press conferences, and minutes are available at https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

[8] The Internet Appendix provides an overview of all scheduled FOMC meetings and PCs between April 2011 and June 2018 along with the FOMC's interest rate decisions.

3. FOMC press conferences and stock returns

In this section, we study the behavior of excess stock returns and portfolio betas on scheduled FOMC announcement days with and without a PC. We show that excess stock returns are higher and increasing in their betas on PC days, but negligible and unrelated to betas on non–PC days. Moreover, we find that the cross-sectional dispersion of portfolio betas significantly declines on PC days using both daily and intraday return data.

3.1. The security market line

We start our empirical analysis by examining how the SML responds to scheduled FOMC meetings with and without a PC relative to all other days. Our main finding is that the SML displays a significantly positive slope on PC days alone, whereas the slope is indistinguishable from zero on all other days. We estimate the intercept and the slope of the SML using the classical Fama and MacBeth (1973) two-step regressions applied to various cross-sections.[9] We consider two types of portfolio betas for the cross-sectional tests. First, we estimate full sample portfolio betas $\widehat{\beta}_j$, indexed by $j = 1, 2, \ldots, N$, by regressing portfolio excess returns on contemporaneous excess market returns using all available observations. Second, we estimate day-specific portfolio betas $\widehat{\beta}_j^D$ using excess return data for each type of day separately to gauge the impact of time variations in portfolio betas on the slope of the SML. We then examine the cross-sectional relationship between portfolio betas and portfolio returns by regressing portfolio excess returns on, respectively, full sample portfolio betas

$$r_{j,t}^D - r_{f,t}^D = \gamma_{0,t}^D + \gamma_{1,t}^D \widehat{\beta}_j + \eta_{j,t}^D \tag{1}$$

and day-specific portfolio betas

$$r_{j,t}^D - r_{f,t}^D = \gamma_{0,t}^D + \gamma_{1,t}^D \widehat{\beta}_j^D + \eta_{j,t}^D, \tag{2}$$

where $\gamma_{0,t}^D$ and $\gamma_{1,t}^D$ are daily estimates of SML intercepts and slopes, respectively, and $\eta_{j,t}^D$ is a cross-sectional pricing error for type of day D. We estimate (1) and (2) separately for non-announcement days, announcement days, PC days, and non–PC days, respectively, and focus on the distinction between PC days and non–PC days.

Panel A of Table 1 presents estimates of the intercept and slope of the SML for ten value-weighted beta-sorted portfolios. On non-announcement days (the majority of days), we observe negligible SML slopes of −1bps for full sample betas and day-specific betas, respectively, and the intercepts are large from both a statistical and an economic perspective. This is consistent with the well known finding that the empirical SML is too flat for beta-sorted portfolios (Black, 1972; Frazzini and Pedersen, 2014). Announcement day SML slopes are positive at 20bps (t-stat of 1.28) using full sample betas and 23bps (t-stat of 1.24) for day-specific betas, but insignificant.

At first glance, this finding seems to be at variance with the results in Savor and Wilson (2014) and Lucca and Moench (2015), but we can easily reconcile our results with those of the existing literature by distinguishing between scheduled meetings with and without a PC. The effect previously associated with announcement days is only present on PC days in our more recent sample period. In particular, the slope of the SML is as high as 34bps (79bps) for full sample (day-specific) betas with a t-statistic of 2.63 (2.81), suggesting a substantially stronger cross-sectional relation between excess returns and betas on PC days. Moreover, we find that PC day intercepts are indistinguishable from zero, and we observe a considerably higher cross-sectional R^2 on PC days relative to other days. For example, we find a cross-sectional R^2 of about 83.29% on PC days, but an R^2 of only 27.69% and 9.95% on non-announcement and non-PC days, respectively, for full sample betas. The numbers are comparable for day-specific betas. In contrast, the slope of the SML is practically zero on non–PC days with insignificant slopes of 6bps (t-stat of 0.19) and 4bps (t-stat of 0.16) for full sample betas and day-specific betas, respectively.

We use a standard t-test to compare means on announcement days, PC days, and non–PC days, respectively, relative to means on non-announcement days and confirm that the slope of the SML is higher on PC days compared to the other types of days. The SML slope on PC days is about 35bps (80bps) higher than on non-announcement days (t-stat of 2.63 (2.82)) for full sample (day-specific) portfolio betas. The differences between announcement and non-announcement days (Δ Announcement) and non–PC days and non-announcement days (Δ Non–PC), respectively, are insignificant. These differences suggest that stock returns are more strongly connected to betas on PC days compared to non-PC days.

The positive slopes, insignificant intercepts, and high cross-sectional R^2 are all consistent with the predictions of the CAPM, but they tell us little about the magnitude of the pricing errors. We address this issue in two steps. First, we compute mean absolute pricing errors (MAPE) for each type of day and find that the MAPE is generally higher for PC days. As Figure 1 illustrates below, this is mainly attributable to a larger cross-sectional variation in returns on PC days compared to all other days. For example, MAPE is low on non-announcement days because there is little heterogeneity in portfolio excess returns. Second, we test whether the cross-sectional pricing errors are jointly equal to zero using the test statistic $T^D \widehat{\boldsymbol{\eta}}_D' \widehat{\boldsymbol{\Sigma}}_{\eta_D}^{-1} \widehat{\boldsymbol{\eta}}_D \sim \chi_{N-1}^2$, where $\widehat{\boldsymbol{\eta}}_D$ is a vector of average pricing errors for type of day D, $\widehat{\boldsymbol{\Sigma}}_{\eta_D}$ is an estimate of the covariance matrix of the sample pricing errors obtained using a Newey and West (1987) estimator, and T^D denotes the sample size for each type of day.[10] The joint test for the null of zero cross-sectional pricing errors rejects on PC days at a 5% (10%) significance level for full sample (day-specific) portfolio betas. As such, the CAPM is formally rejected, although it does provide a much improved description of excess portfolio returns on PC days compared to all other days. In line with the low MAPE, the test does not reject on non-announcement days as pricing errors are generally small. In summary, we conclude that market betas are now only significantly related to the cross-section of beta-sorted portfolio returns on PC days, whereas the previously strong announcement day effect has disappeared on non-PC days.

Figure 1 presents graphical evidence corroborating the results in Table 1. The top panel plots average excess returns (in basis points) for ten value-weighted beta-sorted portfolios against full sample portfolio betas (left panel) and day-specific portfolio betas (right panel) separately for PC days, non–PC days, and non-announcement days, respectively. The slope of the SML is visibly steeper on PC days using both full sample and day-specific portfolio betas, but the effect is more pronounced for day-specfic betas (79bps for day-specific versus 34bps for full sample betas). The graphical and tabulated evidence therefore suggests that allowing for day-specific betas plays an important role in correctly identifying the shape of the SML on PC days, which is partly formed by a compression in portfolio betas towards the value one. Intuitively, and since mean portfolio excess returns are the same, a steeper slope naturally materializes when betas shrink towards the

[9] Cohen et al. (2005), Savor and Wilson (2014), Hong and Sraer (2016), Jylhä (2018), and Hendershott et al. (2020) similarly use the Fama and MacBeth (1973) methodology to estimate the intercept and slope of the SML.

[10] We focus on cross-sectional pricing errors to remain consistent with the cross-sectional interpretation of our results, but provide joint tests for time series intercept in the spirit of Gibbons et al. (1989) in the Internet Appendix.

Table 1

The Security Market Line. This table reports estimates from Fama and MacBeth (1973) regressions of daily value-weighted portfolio excess returns on portfolio betas for ten beta-sorted portfolios (Panel A) and ten beta-sorted, ten IVOL-sorted, and 25 size- and book-to-market-sorted portfolios (Panel B). Portfolio betas are estimated using (i) the full sample of available observations and (ii) using day-specific return data. Estimates are computed separately for non-announcement days, announcement days, announcement days with a press conference (PC days), and announcement days without a PC (non–PC days). We report differences to non-announcement days (denoted with Δ) in the last rows of each panel. Fama-MacBeth t-statistics computed using the standard deviation of the time series of coefficient estimates are reported in square brackets. We also report the cross-sectional R^2 from the Fama-MacBeth regressions and mean absolute pricing errors (MAPE) in basis points on each type of day. Last, we provide the p-value from a χ^2 test for the null that cross-sectional pricing errors are jointly equal to zero in curly brackets. The sample period is April 2011 to June 2018.

	Full sample betas				Day-specific betas			
Type of day	Intercept	Slope	R^2(%)	MAPE	Intercept	Slope	R^2(%)	MAPE
Panel A: Ten beta-sorted portfolios								
Non-announcement days	0.06	−0.01	27.69	0.32	0.06	−0.01	27.54	0.32
	[3.10]	[−0.25]		{0.76}	[3.12]	[−0.25]		{0.75}
Announcement days	−0.03	0.20	84.06	2.63	−0.06	0.23	78.82	2.93
	[−0.28]	[1.28]		{0.68}	[−0.52]	[1.24]		{0.55}
PC days	0.12	0.34	83.29	4.48	−0.35	0.79	86.99	4.55
	[0.85]	[2.63]		{0.01}	[−1.45]	[2.81]		{0.10}
Non–PC days	−0.19	0.06	9.95	5.29	−0.18	0.04	7.26	5.44
	[−1.55]	[0.19]		{0.14}	[−1.54]	[0.16]		{0.13}
Δ Announcement	−0.08	0.21			−0.11	0.23		
	[−0.84]	[1.31]			[−1.01]	[1.26]		
Δ PC	0.07	0.35			−0.40	0.80		
	[0.46]	[2.63]			[−1.68]	[2.82]		
Δ Non–PC	−0.24	0.06			−0.23	0.05		
	[−1.99]	[0.21]			[−2.00]	[0.19]		
Panel B: Ten beta-sorted, ten IVOL-sorted, and 25 size-value portfolios								
Non-announcement days	0.05	−0.00	2.54	0.45	0.05	−0.00	2.47	0.45
	[2.58]	[−0.15]		{0.84}	[2.60]	[−0.15]		{0.84}
Announcement days	−0.00	0.17	33.18	4.22	0.01	0.16	25.93	4.56
	[−0.05]	[0.99]		{0.00}	[0.05]	[0.82]		{0.00}
PC days	0.01	0.46	50.18	7.23	−0.35	0.83	39.35	7.40
	[0.07]	[3.42]		{0.00}	[−1.84]	[3.24]		{0.00}
Non–PC days	−0.02	−0.14	5.21	9.57	−0.07	−0.09	3.10	9.59
	[−0.14]	[−0.42]		{0.00}	[−0.59]	[−0.31]		{0.00}
Δ Announcement	−0.06	0.18			−0.05	0.16		
	[−0.55]	[1.00]			[−0.38]	[0.84]		
Δ PC	−0.04	0.47			−0.40	0.83		
	[−0.29]	[3.37]			[−2.11]	[3.23]		
Δ Non–PC	−0.07	−0.13			−0.12	−0.08		
	[−0.49]	[−0.41]			[−1.00]	[−0.29]		

mean.[11] This result is at odds with an existing literature that finds no significant differences in betas across days (e.g., Savor and Wilson (2014)) and suggests that the compression of betas is a novel phenomenon related to our sample period in which the FOMC held PCs after only a subset of their meetings.

Panel B of Table 1 confirms our conclusions in a broader cross-section augmented with ten IVOL-sorted portfolios (Ang et al., 2006; 2009) and 25 portfolios sorted on size and book-to-market equity ratios (Fama and French, 1992). The PC day slope is 46bps (t-stat of 3.42) and 83bps (t-stat of 3.24) for full sample and day-specific betas, respectively, whereas the slopes are small and insignificant on all other days. The PC day difference is likewise significant. Last, the cross-sectional R^2 on PC days is similarly high at 50.18% compared to a non-PC day R^2 of 5.21% for full sample betas and 39.25% relative to 3.10% for day-specific betas. The joint test reject the null of joint zero pricing errors for all days except non-announcement days, where MAPEs and pricing errors are small in magnitude. The bottom panels of Figure 1 largely mirror the conclusion from its top panels. The slope of the SML is higher on PC days, and this effect is more pronounced for day-specific betas. This steeper slope for day-specific betas is again caused by a clear compression of betas towards one for this broader cross-section as well. We arrive at identical conclusions using equal-weighted portfolio returns and when using rolling-window betas as in Savor and Wilson (2014) in the Internet Appendix. All together, our empirical findings suggest that excess stock returns are increasing in portfolio betas and that the cross-sectional dispersion of betas declines substantially on PC days. We investigate time variations in portfolio betas in more detail below.

3.2. Variation in portfolio betas

The graphical evidence in Fig. 1 suggests that portfolio betas tend to compress towards the value one on PC days. Time variations in betas is a relevant issue to address when studying announcement premiums (see, e.g., Patton and Verardo (2012) and Savor and Wilson (2016)) as they constitute an important and potential explanation for the high returns. While earlier evidence points to day invariant betas (Savor and Wilson, 2014; Wachter and Zhu, 2021), this section provides new empirical evidence that portfolio betas indeed change markedly on PC days over the period from April 2011 to June 2018.

Table 2 presents estimates of portfolio betas for value-weighted portfolios sorted on betas, IVOL, and size and book-to-market equity ratios, respectively. For each portfolio j, we consider a regression in which the intercept and the portfolio beta are allowed to

[11] Andrei et al. (2020) develop a theoretical model in which the SML is perceived to be too flat by the empiricist due to an informational distortion that is corrected on announcement days. The central prediction of their model is therefore that important public announcement days (such as FOMC announcement days) should be accompanied with a strong beta compression.

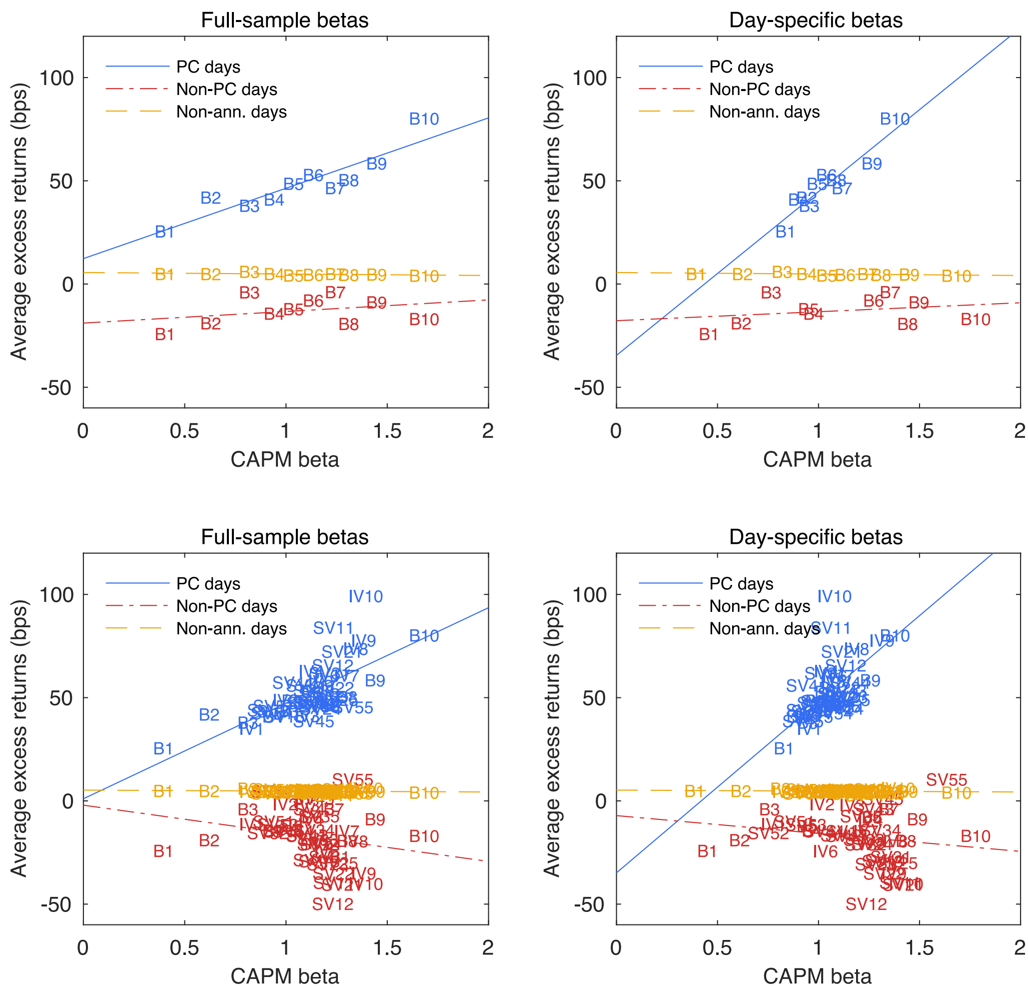

Fig. 1. Average excess portfolio returns. This figure plots average daily excess returns in basis points (bps) against full sample portfolio betas (left panel) and day-specific portfolio betas (right panel) along with implied estimates of the Security Market Lines for ten value-weighted beta-sorted portfolios (top panel) and additionally for ten IVOL-sorted portfolios and 25 size- and book-to-market-equity-sorted portfolios (bottom panel) separately for announcement days with a press conference (PC days, blue entries and solid line), announcement days without a PC (non–PC days, red entries and dash-dotted line), and non-announcement days (yellow entries and dashed line). The sample period is April 2011 to June 2018. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

vary conditional on the type of day

$$\begin{aligned} r_{j,t} - r_{f,t} &= \alpha_{\text{Non-ann},j} + \alpha_{\text{PC},j}\mathbf{1}_{\text{PC}} + \alpha_{\text{Non-PC},j}\mathbf{1}_{\text{Non-PC}} \\ &\quad + \left(\beta_{\text{Non-ann},j} + \beta_{\Delta\text{PC},j}\mathbf{1}_{\text{PC}} + \beta_{\Delta\text{Non-PC},j}\mathbf{1}_{\text{Non-PC}}\right)\left(r_{M,t} - r_{f,t}\right) \\ &\quad + \varepsilon_t, \end{aligned} \tag{3}$$

where $\mathbf{1}_{\text{D}}$ is an indicator for the Dth type of day, $r_{M,t} - r_{f,t}$ is the market excess return, $\beta_{\text{Non-ann},j}$ represents the non-announcement day beta, and $\beta_{\Delta\text{PC},j}$ and $\beta_{\Delta\text{Non-PC},j}$ measure the change in portfolio betas on PC days and non–PC days, respectively. These betas are equivalent to the day-specific betas in Fig. 1. For example, the PC day portfolio betas are given by $\beta_{\text{Non-ann},j} + \beta_{\Delta\text{PC},j}$ and the non-PC day portfolio betas by $\beta_{\text{Non-ann},j} + \beta_{\Delta\text{Non-PC},j}$.

Panel A of Table 2 presents beta estimates from (3) for ten value-weighted beta-sorted portfolios (we omit intercepts to save space). In line with the graphical presentation, we find that the portfolio beta for the portfolio consisting of low-beta stocks increases by 0.44 (t-stat of 3.56) and that the portfolio beta for high-beta stocks declines with −0.30 (t-stat of −2.22) on PC days. More generally, the results are consistent with a compression of betas towards one on PC days, where the magnitude of the change $\beta_{\Delta\text{PC},j}$ in absolute value is increasing in the relative distance to the unit value on non-announcement days. Put differently, portfolios with relatively lower (higher) betas experience the biggest increase (decline) on PC days. This observation, taken together with our previous results that stocks earn higher returns on PC days that are increasing in their betas, presents a puzzle. We are not aware of any model that can rationalize the combined finding that all portfolios earn higher excess returns on the same day that betas compress towards one.

Panels B and C of Table 2 demonstrate that portfolio betas for ten IVOL-sorted portfolios and 25 size- and book-to-market equity-sorted portfolio similarly compress on PC days. In particular, portfolios with relatively high (low) betas on non-announcement days tend to experience a decline (increase) in the value of their betas on PC days. Put differently, beta compression is a robust finding on PC days and is not limited to beta-sorted portfolios. Moreover, this behavior rules out the possibility that our results are due to generic large market move days where stocks with higher betas co-move more with the market.

Figure 2 complements the above analysis by plotting the cross-sectional dispersion in portfolio betas for the portfolios considered in Table 2 for PC days, non–PC days, and non-announcement days, respectively. We follow Andersen et al. (2020) and compute the cross-sectional dispersion in portfolio betas as

$$\text{Disp}_D = \frac{1}{N}\sum_{j=1}^{N}\left(\beta_{D,j} - 1\right)^2, \tag{4}$$

Table 2

Stock market betas. This table reports estimates from the regression in (3) in which we regress value-weighted excess portfolio returns on a constant, the stock market excess return, a PC day dummy, a non–PC day dummy, and the respective interactions between the market excess return and the dummies. We only report coefficients for the market return and the interactions, which corresponds to the market beta on non-announcement days (as a benchmark) and the changes in betas on PC days and non–PC days, respectively. Panel A presents the results for ten beta-sorted portfolios, Panel B for ten IVOL-sorted portfolios, and Panel C for 25 size- and book-to-market-sorted portfolios. Newey and West (1987) t-statistics are reported in square brackets. The sample period is April 2011 to June 2018.

	Low	2	3	4	5	6	7	8	9	High
Panel A: Ten beta-sorted portfolios										
Non-ann.	0.39	0.62	0.81	0.93	1.03	1.13	1.24	1.30	1.44	1.69
	[17.40]	[34.44]	[61.82]	[80.81]	[92.70]	[72.35]	[55.37]	[59.97]	[53.93]	[44.39]
ΔPC	0.44	0.32	0.13	−0.04	−0.05	−0.09	−0.13	−0.22	−0.18	−0.30
	[3.56]	[3.62]	[2.69]	[−1.24]	[−1.11]	[−1.55]	[−1.76]	[−2.58]	[−2.00]	[−2.22]
ΔNon-PC	0.06	−0.01	−0.05	0.03	−0.09	0.14	0.11	0.13	0.05	0.09
	[1.28]	[−0.12]	[−0.89]	[0.86]	[−3.56]	[2.68]	[2.24]	[2.81]	[0.96]	[1.11]
Panel B: Ten IVOL-sorted portfolios										
Non-ann.	0.83	0.99	1.10	1.12	1.17	1.21	1.30	1.34	1.38	1.39
	[63.36]	[123.28]	[95.57]	[67.05]	[69.47]	[68.18]	[49.74]	[46.67]	[51.72]	[31.70]
ΔPC	0.12	0.08	−0.16	−0.08	−0.10	−0.13	−0.19	−0.15	−0.07	−0.31
	[2.35]	[1.08]	[−4.19]	[−1.73]	[−1.33]	[−1.37]	[−2.34]	[−1.24]	[−0.50]	[−1.52]
ΔNon-PC	−0.05	0.02	0.06	0.14	0.10	−0.17	−0.07	0.04	−0.01	0.04
	[−1.63]	[0.82]	[0.77]	[3.34]	[2.81]	[−3.24]	[−0.75]	[0.62]	[−0.11]	[0.25]

		Growth	2	3	4	Value
Panel C: 25 size-value portfolios						
Non-ann.	Small	1.23	1.23	1.16	1.13	0.98
		[35.50]	[36.21]	[36.50]	[30.32]	[35.82]
ΔPC		−0.17	−0.10	−0.06	−0.07	−0.02
		[−1.11]	[−0.66]	[−0.56]	[−0.60]	[−0.14]
ΔNon-PC		0.17	0.01	0.16	0.20	0.15
		[1.38]	[0.05]	[1.66]	[2.18]	[1.96]
Non-ann.	2	1.27	1.23	1.20	1.17	1.25
		[44.93]	[39.82]	[38.88]	[43.99]	[35.10]
ΔPC		−0.16	−0.13	−0.06	−0.05	−0.10
		[−1.17]	[−1.25]	[−0.83]	[−0.52]	[−0.68]
ΔNon-PC		0.15	0.09	0.08	0.09	0.14
		[1.25]	[1.26]	[1.00]	[1.50]	[1.44]
Non-ann.	3	1.21	1.15	1.15	1.13	1.16
		[58.54]	[48.52]	[56.80]	[47.88]	[56.60]
ΔPC		−0.18	−0.14	−0.15	−0.05	−0.06
		[−2.10]	[−1.94]	[−1.78]	[−0.45]	[−0.44]
ΔNon-PC		0.15	0.08	0.07	0.17	0.05
		[1.73]	[1.59]	[0.84]	[3.03]	[0.41]
Non-ann.	4	1.10	1.10	1.13	1.03	1.13
		[72.97]	[69.46]	[65.10]	[68.66]	[64.75]
ΔPC		−0.16	−0.11	0.00	0.12	−0.21
		[−2.89]	[−1.94]	[0.03]	[1.42]	[−1.98]
ΔNon-PC		0.03	0.01	0.14	−0.01	0.18
		[0.43]	[0.21]	[3.14]	[−0.13]	[3.39]
Non-ann.	Large	0.94	0.91	0.96	0.92	1.32
		[81.54]	[84.24]	[115.48]	[100.31]	[44.89]
ΔPC		0.09	0.03	0.01	0.14	−0.25
		[1.26]	[0.76]	[0.11]	[1.91]	[−1.84]
ΔNon-PC		−0.06	−0.16	−0.02	0.06	0.31
		[−1.43]	[−5.92]	[−0.45]	[1.69]	[3.42]

where N is the number of portfolios, and $\beta_{D,j}$ denotes the beta for portfolio j on type of day D.[12] The results are clear: the cross-sectional dispersion in portfolio betas is orders of magnitude lower on PC days relative to all other days. This observation is consistent across all the cross-sections of stocks considered here. Overall, the evidence strongly points to time variations in betas over our sample period and, as a results, represents a challenge for models of the announcement day premium that assume constant portfolio betas.

The fact that our results differ from those of Savor and Wilson (2014) may reflect two aspects of the empirical design. First, Savor and Wilson (2014) include a host of macroeconomic announcements beyond FOMC announcements in their analysis. Second, changing betas could be a feature of our more recent sample period. In the Internet Appendix, we study portfolio betas over the period 1994–2011 and find no significant differences on announcement days, suggesting that time variation in betas is a phenomenon new to the PC communication period.

3.3. Evidence from intraday return data

Andersen et al. (2020) show that the cross-sectional dispersion in betas generally declines during the trading day and that the decline is stronger on days with scheduled FOMC meetings. In this section, we provide additional evidence from intraday data that the reduction in the cross-sectional dispersion in portfolio betas is more pronounced on PC days.

3.3.1. Estimating intraday portfolio betas

We examine the dynamics of intraday portfolio betas in a setting that closely matches our daily setting above. We start

[12] Andersen et al. (2020) define dispersion on a stock level, while we consider dispersion at the portfolio level to remain comparable with the literature on announcement day effects.

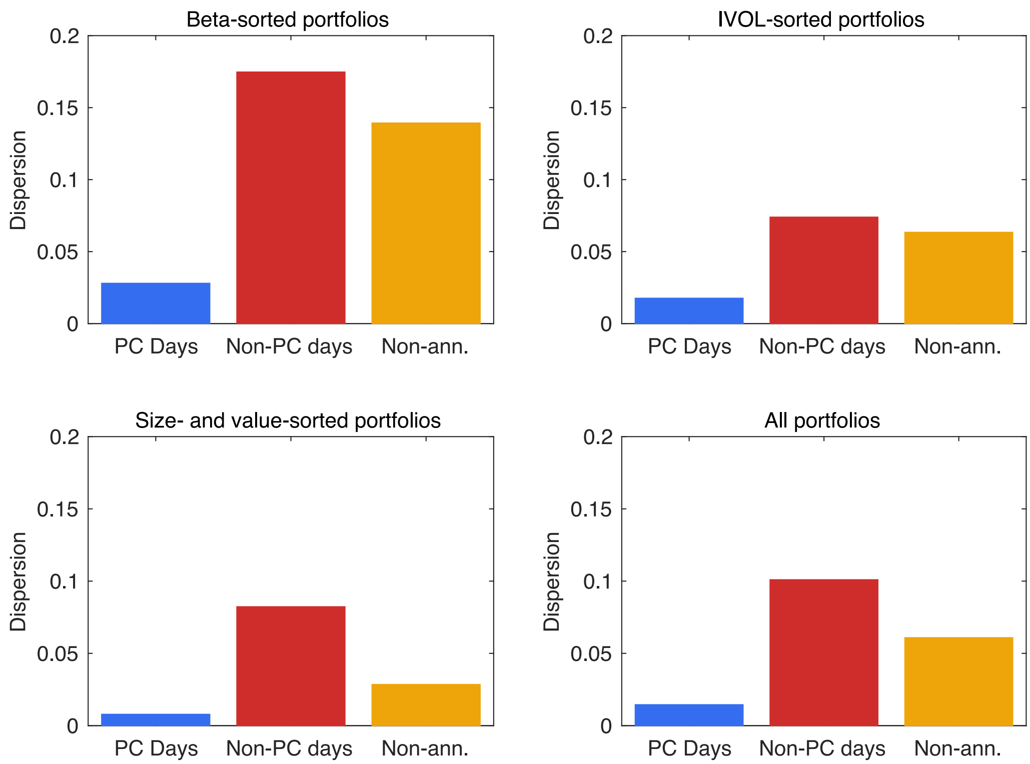

Fig. 2. Beta dispersion. This figure plots the cross-sectional dispersion in estimated portfolio betas for ten beta-sorted portfolios (top left), ten IVOL-sorted portfolios (top right), 25 size- and book-to-market-equity-sorted portfolios (bottom left), and all portfolios together (bottom right) separately for announcement days with a press conference (PC days), announcement days without a PC (non–PC days), and non-announcement days. Betas are estimated using the regression in (3). All portfolio returns are value-weighted. The sample period is April 2011 to June 2018.

by collecting intraday data on individual stocks from TAQ and prepare the data following the cleaning procedure of Barndorff-Nielsen et al. (2009) to ensure good data quality. We then exclude stocks with a share price below $5 (as above) and stocks traded less than once every 15 min during the active opening hours to ensure sufficient liquidity. Our intraday dataset contains a total of 5,431 stocks with an average (median) of 2,476 (2,488) stocks each day that matches the requirements. The minimum (maximum) number of stocks each day is 2,202 (2,827).

To remain comparable with our previous analysis, we build ten equally sized and value-weighted beta-sorted portfolios. We estimate realized betas using intraday return data and form portfolios by ranking and sorting individual stocks according to this beta. We follow Andersen et al. (2020) and estimate intraday stock betas using a truncation approach (Mancini, 2001; 2009). The realized beta for each stock is computed with respect to the S&P500 index tracking exchange traded fund, SPDR (ticker symbol SPY), which is the standard proxy for the aggregate market portfolio in the high-frequency literature. We compute realized betas for each stock by dividing the realized covariance between the individual stock and the market portfolio (SPY) with the realized variance of the market portfolio. We use a five minute sampling frequency for the realized variance of the market portfolio and a ten minute sampling frequency for the realized covariance. On the latter, we double the length of the high-frequency increments to reduce the impact of non-synchronous trading originating from the lower liquidity of individual assets relative to the market index, which would otherwise downward bias estimates of the covariation.

With the ten intraday-beta-sorted portfolios in hand, we then compute post-ranking realized intraday portfolio betas following the procedure described above, but using instead a three minute sampling frequency for the realized variance of the market portfolio as well as for the realized covariance between each portfolio and the market index. We base our intraday analysis on rolling window estimates of these betas around FOMC announcements. The Internet Appendix provides full details of the estimation procedures.

3.3.2. Intraday variation in portfolio betas

Figure 3 plots the average intraday cross-sectional dispersion in portfolio betas computed using (4) based on a rolling window of one hour using a three minute sampling frequency for the intraday returns around scheduled FOMC announcements separately for PC days, non–PC days, and non-announcement days, respectively. Consistent with our previous evidence, we find that the reduction in the cross-sectional beta dispersion is more pronounced on PC days relative to all other days. The cross-sectional beta dispersion is noticeably more elevated in the beginning of the day when the FOMC announcement is followed by a PC and then declines substantially during the trading hours. The decline in dispersion is particularly pronounced around the announcement time. While we observe a reduction in the cross-sectional beta dispersion on non–PC days as well using intraday data, it is not as prominent as the decline observed on PC days. On non-announcement days, we observe the same slowly declining cross-sectional beta dispersion during the trading day as documented and discussed in Andersen et al. (2020).

The bottom panel of Fig. 3 plots the realized intraday portfolio betas around FOMC announcements for each type of day. If our empirical findings for the intraday pattern is to be consistent with the daily regressions in Table 2, we should see a uniform compression in portfolio betas towards the unit value around the announcement time. Indeed, we observe a strong compression in portfolio betas that is especially pronounced for the extreme portfolios on PC days. In sum, we provide evidence of a reduction in the cross-sectional

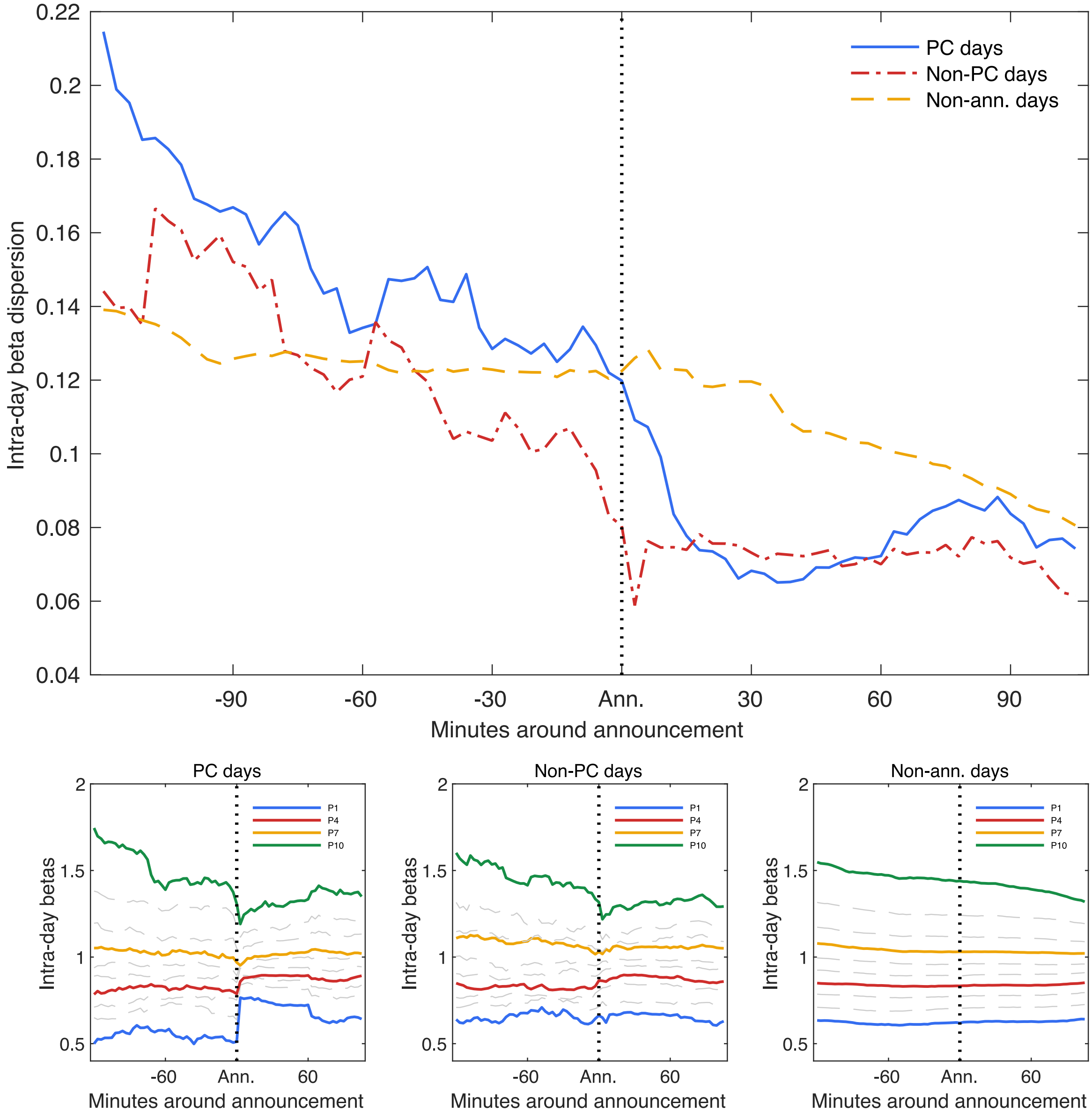

Fig. 3. Intraday beta dispersion. This figure plots the intraday evolution of the cross-sectional dispersion in portfolio betas for ten equally sized beta-sorted portfolios (top panel) and the intraday behavior of portfolio betas (bottom panels) around scheduled FOMC announcements (dashed vertical line). We display results separately for announcement days with a press conference (PC days), announcement days without a PC (non–PC days), and non-announcement days. We use 2pm ET as the announcement time for non-announcement days, which is the time of the day where the majority of the announcements are released. All portfolio returns are value-weighted. We highlight the beta dynamics for the portfolios P1, P4, P7, and P10, but show the remaining using dashed gray lines. The sample period is April 2011 to June 2018.

beta dispersion over the trading day that is visibly stronger on days with FOMC announcements and PCs in particular.

3.3.3. Time series of intraday beta dispersion

The previous section establishes that the intraday evolution of the cross-sectional portfolio beta dispersion declines more strongly on scheduled FOMC announcement days and that the decline is more pronounced when the announcement is followed by a PC. To study the potential determinants of beta compressions on FOMC announcement days more formally, we conduct a time series regression analysis in which the dependent variable is the change in the level of the cross-sectional beta dispersion over a window starting 15 min prior to the announcement to 60 min after the announcement. We regress the change in the level of beta dispersion on explanatory variables capturing market uncertainty, economic and monetary policy uncertainty, and yield curve factors as proxies for market expectations of future monetary policy decisions. All variables are standardized to facilitate comparison and interpretation of the coefficients.

Table 3 presents the regression results. We first assess whether the evolution of the cross-sectional beta dispersion around the FOMC announcement is related to equity market uncertainty. We do this by using the VIX index measured at the market close two days prior to the announcement (to avoid overlap with the pre-FOMC announcement drift of Lucca and Moench (2015)). VIX is a strongly significant predictor (t-stat of 3.40), and a higher VIX value is associated with a smaller reduction in the cross-sectional beta dispersion around FOMC announcements. We obtain a similar effect for bond market uncertainty using the TYVIX index (Choi et al., 2017), although it is insignificant at conventional levels. Column (3) considers the economic policy uncertainty (EPU) index of Baker et al. (2016), measured two days prior to the scheduled announcement, and finds a significantly negative relation (t-stat of −2.04). That is, higher EPU is associated with

Table 3
Beta dispersion regressions. This table report estimates from regressing changes in the level of the cross-sectional beta dispersion from 15 min prior to the announcement to 60 min after the announcement on various explanatory variables: the VIX index, the TYVIX index, the economic policy uncertainty (EPU) index of Baker et al. (2016), the meeting-specific monetary policy uncertainty (MPU) index of Husted et al. (2020), and level, slope, and curvature, which are the first three principal components from the cross-section of daily one through five year zero-coupon Treasury bond yields obtained from Gürkaynak et al. (2007). All variables are lagged two day with respect to the FOMC announcement day except for MPU which is computed as the change from the previous meeting. All explanatory variables are standardized to facilitate comparison. Newey and West (1987) t-statistics are presented in square brackets. The sample period is April 2011 to June 2018.

	(1)	(2)	(3)	(4)	(5)	(6)
VIX	0.03					0.02
	[3.40]					[3.39]
TYVIX		0.02				
		[1.46]				
EPU			−0.02			−0.02
			[−2.04]			[−2.29]
MPU				0.01		
				[1.63]		
Level					−0.03	−0.02
					[−2.69]	[−3.09]
Slope					0.02	0.01
					[1.93]	[0.90]
Curv					0.01	
					[0.45]	
Constant	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04
	[−4.46]	[−4.12]	[−3.53]	[−3.49]	[−4.39]	[−5.70]
R^2(%)	9.15	4.32	4.70	0.89	12.98	23.23

a larger compression of betas around FOMC announcements. Using changes to the meeting-specific monetary policy uncertainty (MPU) index of Husted et al. (2020) reveals a positive, but insignificant, coefficient. That is, changes in monetary policy uncertainty *between* meetings has little effect on beta dispersion.[13] Last, in column (4), we gauge whether beta dispersion is related to the first three principal components (level, slope, and curvature) from the cross-section of Treasury yields using zero-coupon yields from Gürkaynak et al. (2007) two days before the announcement. The level enters with a negative coefficient (t-stat of −2.69) and the slope with a positive coefficient (t-stat of 1.93). Curvature is insignificant. Thus, market expectations about both the level and the future path of monetary policy (the slope) is associated with the cross-sectional distribution of betas, although the level factor seems more important. The latter is confirmed in column (5) where we consider all significant variables jointly. VIX, EPU, and level factor remain significant and with consistent signs, but the slope factor turns insignificant. Overall, these variables are able to explain about 23% of the variation in the cross-sectional dispersion in betas around FOMC announcements.

3.4. Resolution of uncertainty

A potential explanation for the different dynamics of excess stock returns and betas on PC days is that the FOMC provides new information about the path of monetary policy and/or macroeconomic prospects. For example, Andrei et al. (2020) and Andersen et al. (2020) argue that the release of new market-wide information can lower the cross-sectional beta dispersion. To corroborate these points, we explore a range of popular uncertainty proxies: (i) VIX, (ii) TYVIX, (iii) EPU, and (iv) MPU. If market reactions and expectations are shaped by the arrival of new information, then we should see a reduction in uncertainty on PC days, but not on non–PC days.

Table 4
Uncertainty measures. This table reports estimates from regressing log changes to the VIX index (Panel A), the TYVIX index (Panel B), and the economic policy uncertainty (EPU) index of Baker et al. (2016) (Panel C) in percent onto a constant, the market excess return, an indicator for the type of day, and an interaction term between the market returns and the type of day. We consider regressions for announcement days, announcement days with a press conference (PC days), and announcement days without a PC (non–PC days). Panel D reports log changes of the meeting-specific monetary policy uncertainty (MPU) index of Husted et al. (2020) in percent. Newey and West (1987) t-statistics are presented in square brackets. The sample period is April 2011 to June 2018.

	Type of day		
	Announcement days	PC days	Non-PC days
Panel A: VIX			
Constant	0.39	0.38	0.35
	[3.65]	[3.59]	[3.26]
Market return	−6.68	−6.64	−6.69
	[−23.60]	[−24.01]	[−23.93]
Type of day	−1.78	−2.65	−0.56
	[−3.13]	[−3.29]	[−0.78]
Interaction	0.42	0.06	0.96
	[0.79]	[0.06]	[1.55]
R^2(%)	63.60	63.62	63.49
Panel B: TYVIX			
Constant	0.14	0.11	0.05
	[1.45]	[1.09]	[0.54]
Market return	−1.05	−1.00	−1.13
	[−7.12]	[−6.83]	[−7.56]
Type of day	−3.86	−4.28	−1.84
	[−5.85]	[−3.83]	[−2.80]
Interaction	0.02	−2.57	1.78
	[0.03]	[−2.51]	[2.50]
R^2(%)	6.80	7.26	5.33
Panel C: EPU			
Constant	0.27	0.28	0.10
	[0.38]	[0.40]	[0.14]
Market return	−2.82	−2.76	−2.52
	[−2.05]	[−2.05]	[−1.83]
Type of day	−6.33	−22.87	0.81
	[−0.95]	[−1.82]	[0.11]
Interaction	8.07	28.28	1.55
	[1.60]	[2.15]	[0.36]
R^2(%)	0.31	0.58	0.20
Panel D: MPU			
Type of day		−12.62	16.58
		[−3.30]	[3.26]

Table 4 presents results from regressing log changes to the uncertainty measures onto stock market excess returns, a day-specific dummy, and the interaction term between the two. We consider separate regressions for FOMC announcement days, non–PC days, and PC days, respectively. We opt for simple log changes to MPU as it is meeting specific. Overall, we find consistent evidence that uncertainty declines on PC days, but not on non–PC days, which supports an information channel for the stronger stock market response on PC days.

Starting with log VIX returns in Panel A, we find the well-established negative relation between market excess returns and changes in implied volatility.[14] Across specifications, we find that a 1% increase in excess returns is associated with more than a 6% reduction in the (log) VIX (t-stats of about 24 on average).

[13] The economic policy uncertainty index is obtained from https://www.policyuncertainty.com, and the monetary policy uncertainty index is available from https://sites.google.com/site/lucasfhusted/data.

[14] For example, Campbell and Hentschel (1992) find that volatility tends to be higher after stock market declines, which implies a negative correlation between stock returns and future volatility.

VIX declines about 1.8% (t-stat of −3.13) on days with scheduled FOMC announcements. However, separating announcement days into days with and without a PC, respectively, reveals a remarkable contrast between the two types of days. While there is only a negligible and insignificant decline of 0.56% in VIX on non–PC days, we find a sizable and significant average decline of 2.65% (t-stat of −3.29) on PC days.[15] Panel B similarly shows that TYVIX declines more on PC days (about 4.28%) relative to non–PC days (about 1.84%). Moreover, the interaction terms are significant for both types of days, and the results suggest that TYVIX betas become positive on non–PC days. We discuss interpretations of this observation in Section 4.2.

VIX and TYVIX are market-based measures. In contrast, the EPU is based on textual analysis of keywords in newspaper coverage. Panel C shows that EPU declines with about 23% on PC days, which is economically meaningful, although only significant at the 10% level. Last, in Panel D, we find that MPU declines with about 12% on PC days and increases with about 16% on non–PC days. MPU is a news-based index of monetary policy uncertainty that captures the degree of uncertainty that the public perceives about Federal Reserve policy actions and their consequences, and we clearly note that such uncertainties are lower on PC days. Overall, the empirical results are consistent with the hypothesis that the higher PC days excess returns, the steeper SML slope, and the lower beta dispersion may originate from the FOMC providing more price-relevant information on announcement days with a PC, which results in substantial declines in uncertainty.

4. Evidence from bond and currency markets

This section first examines the behavior of Treasury bonds on PC and non–PC days. We find that Treasury bond excess returns are negatively related to their bond betas on the majority of days, which is consistent with a hedging premium (Cieslak and Pang, 2020), but positively related to their bond betas on PC days. This gives rise to time variation and sign-switches in stock-bond correlations that are associated with uncertainty and yield curve information. We close the section by studying the PC day effect for currency portfolios sorted on interest rate differentials (Lustig et al., 2011; Mueller et al., 2017).

4.1. Treasury bond excess returns

Figure 4 plots average Treasury bond excess returns against betas for bonds with maturities of one, two, five, seven, ten, 20, and 30 years, where bond betas are estimated by regressing excess bond returns onto contemporaneous excess stock market returns. Treasury bond returns are obtained from CRSP's Daily Treasury Fixed Term Indexes file and we compute excess returns using the one-month Treasury bill rate from Kenneth French's data library.

Treasury bond excess returns are positive and increasing in the bond's duration on all days. Consistent with Lucca and Moench (2015), we find no significant differences between bond returns on non-announcement days, non–PC days, and PC days.[16] The empirical finding that stocks, but not bonds, earn high returns on FOMC announcement days has long been considered a puzzle in the literature. Cieslak and Pang (2020) provide a recent explanation by decomposing the overall stock and bond price response into components related to monetary news, growth news, and two distinct shocks (see also Cieslak and Schrimpf (2019)). The shocks generate two time-varying risk premiums: a common risk premium and a hedging risk premium. Importantly, the two risk premium shocks affect stocks and bonds differently. Positive common premium shocks lower both stock and bond prices through a discount rate channel. Positive hedging premium shocks, on the other hand, lower (increase) the risk premium on bonds (stocks) through a cash flow channel. Thus, common (hedging) premium shocks produce positive (negative) stock-bond correlations.

Figure 4 illustrates that Treasury bond betas are negative on non-announcement days. The negative bond betas for our sample period is consistent with a large literature that finds that Treasury bonds have been viewed as hedge assets since the late 1990s (Campbell et al., 2017; 2020; Kozak, 2019) and the increased role of the hedging premium shocks from the late 1990s and onwards discussed in Cieslak and Pang (2020). Treasury bond betas remain negative on non–PC days, but increase significantly and turn positive on PC days. Savor and Wilson (2013) similarly find that bond betas differ markedly across announcement days, and this change in bond betas is a central feature in the announcement day model of Wachter and Zhu (2021). Our finding complements this literature by uncovering a differential behavior on PC days and non-PC days. The negative SML slope on non–PC days indicates that investors view Treasury bonds as hedge assets, whereas the positive slope on PC days suggests that bonds are viewed as risky. That is, bonds co-vary positively with stocks on PC days, but not on other days. The slightly larger, but insignificant, excess returns on non–PC days are consistent with a lower value of the hedging premium (Cieslak and Pang, 2020). We turn to a more in-dept discussion of the drivers of the stock-bond relation in the next section.

4.2. Stock-bond correlations

This section provides further details on the relationship between stocks and bonds by studying an important quantity in the financial literature: the stock-bond correlation.[17]

Table 5 reports full sample realized stock-bond correlations on non-announcement days and changes to correlations on PC days and non–PC days, respectively, along with Newey and West (1987) t-statistics. Non-announcement day stock-bond correlations are negative and decreasing with bond maturity (as betas in Fig. 4). On non–PC days, there are few significant changes to correlations. The one-year bond is the exception, where the stock-bond correlation increases significantly and becomes positive. The remaining negative stock-bond correlations, taken together with unresolved uncertainty (Table 4), positive bond returns, and negative stock returns, is consistent with a hedge asset channel for Treasury bonds in which risk averse investors drive down the prices of risky assets and the prices of hedge assets up in a "*flight-to-safety*"-type mechanism (Baele et al., 2020).[18] Similarly, Cieslak and Pang (2020) find that an increase in the importance of the hedging premium shocks has taken place since the late 1990s and that this increase can explain the shift from positive to negative stock-bond correlations because hedging premium shocks drive stock and bond returns in opposite directions. As such, a decline (increase) in the importance of the hedge (common) premium on PC

[15] We treat VIX as an uncertainty measure following the tradition in the literature (see, e.g., Savor and Wilson (2013), Boguth et al. (2019), and Brusa et al. (2020)), but note that VIX additionally contains a risk aversion component (Bekaert et al., 2013).

[16] Descriptive statistics and SML estimation results for Treasury bonds are tabulated in the Internet Appendix.

[17] See also Ilmanen (2003), Connolly et al. (2005), Andersen et al. (2003, 2007), Christiansen and Ranaldo (2007), Baele et al. (2010), Song (2017), Ermolov (2018), Adrian et al. (2019), Baele et al. (2020), and Campbell et al. (2020) for papers studying time variations and sign-switches in stock-bond correlations.

[18] Baele et al. (2020) define a flight-to-safety event as a day on which bond returns are positive, equity returns are negative, the stock-bond return correlation is negative, and there is market stress. This corresponds well with non–PC days.

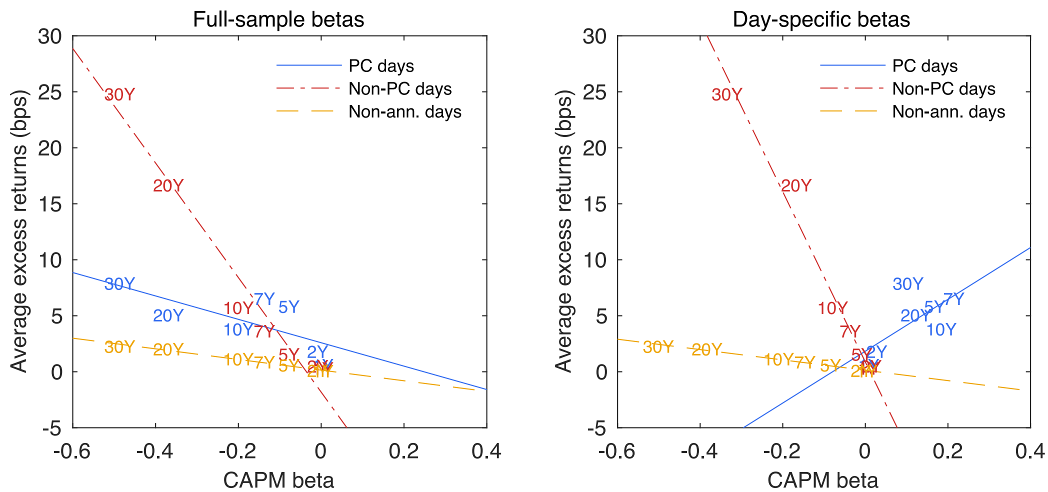

Fig. 4. Average excess Treasury bond returns. This figure plots average daily excess returns in basis points (bps) against full sample portfolio betas (left panel) and day-specific portfolio betas (right panel) along with implied estimates of the Security Market Lines for seven Treasury bonds with maturities, one, two, five, seven, ten, 20, and 30 years separately for announcement days with a press conference (PC days, blue entries and solid line), announcement days without a PC (non–PC days, red entries and dash-dotted line), and non-announcement days (yellow entries and dashed line). The sample period is April 2011 to June 2018.

Table 5

Stock-bond correlations. This table reports realized stock-bond correlations between stock market excess returns and Treasury bond excess returns for bonds with different maturities. We report correlations for non-announcement days as the benchmark and changes in stock-bond correlations on announcement days with a press conference (PC days) and announcement days without a PC (non–PC days). Newey and West (1987) *t*-statistics are presented in square brackets. The sample period is April 2011 to June 2018.

Beta	1Y	2Y	5Y	7Y	10Y	20Y	30Y
Non-ann.	−0.11	−0.30	−0.41	−0.45	−0.49	−0.50	−0.49
	[−3.58]	[−8.79]	[−14.08]	[−15.11]	[−15.01]	[−13.97]	[−13.45]
ΔPC	0.21	0.49	0.73	0.76	0.76	0.64	0.58
	[1.07]	[2.50]	[3.40]	[3.56]	[3.59]	[3.44]	[3.32]
ΔNon-PC	0.33	0.47	0.33	0.28	0.26	0.21	0.11
	[3.24]	[1.86]	[1.20]	[1.00]	[0.88]	[0.66]	[0.33]

days can explain why stock-bond correlations turn positive on PC days and respond differently across the maturity spectrum. The observation that uncertainty drops on PC days, but not on non–PC days, and that the TYVIX beta turns positive on non–PC days (see Table 4) further supports this interpretation.

4.3. Determinants of stock-bond correlations

Table 6 examines the sources of time variations in stock-bond correlations. We estimate realized stock-bond correlations using a one-year rolling window of daily returns and focus on scheduled FOMC announcement days. Announcement day stock-bond correlations are then regressed onto the same set of economic variables considered in Section 3.3.3.

Panel A of Table 6 presents results from regressing announcement day stock-bond correlations onto standardized values of VIX and TYVIX two days prior to the announcement. VIX is significantly negatively related to the stock-bond correlations for bonds in the medium-term yield curve, whereas TYVIX is strongly significant and positively related to the stock-bond correlation for the one-year bond. These differential exposures to stock and bond market uncertainty may therefore help explain the differential stock-bond reactions observed in Table 5 for PC and non–PC days. Panel B considers EPU and MPU. Most coefficients are negative, although insignificant at conventional levels. That stock-bond correlations decrease as a response to heightened economic and monetary policy uncertainty is intuitive and highlights the hedging value of bonds. Panel C presents results for level, slope, and curvature factors that represent information embedded in the term structure. The level factor is negatively associated with stock-bond correlations at the very short end of the term structure and positively associated with longer-term stock-bond correlations. Fundamentally, the exposure to the level factor can help explain why stock-bond correlations for different maturities react differently on announcement days. The slope factor is similarly significant with a positive coefficient, suggesting that stock-bond correlations increase when investors expect the FOMC to loosen policy. Curvature does not seem to play a significant role in determining stock-bond correlations. In sum, stock-bond correlations in the short-end of the term structure tend to be lower when TYVIX is low, the level of interest rates is high, and the FOMC is expected to loosen policy. Stock-bond correlations in the longer-end of the term structure tends to be low when VIX is high, interest rates are low, and the FOMC is expected to loosen policy.

4.4. Currency excess returns

Mueller et al. (2017) provide evidence that foreign exchange rates and currency portfolios sorted on interest rate differentials (Lustig et al., 2011) respond strongly to scheduled FOMC announcements. Here, we investigate whether the introduction of PCs affects the way foreign exchange market participants react to monetary policy announcements. To do so, we collect daily spot and one-month forward rates for nine currencies quoted against the U.S. dollar: Australia, Canada, Euro, Japan, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom (the G10 currencies). This sample represents a selection of the most traded and liquid currencies (Bank for International Settlements, 2019). All data are collected from Barclays and Reuters (via Datastream). The excess return to buying a foreign currency in the forward

Table 6

Determinants of stock-bond correlations. This table reports estimates from regressing realized FOMC announcement day stock-bond correlations on various explanatory variables. Panel A presents results for the VIX index and the TYVIX index. Panel B presents results for the economic policy uncertainty (EPU) index of Baker et al. (2016) and the meeting-specific monetary policy uncertainty (MPU) index of Husted et al. (2020). Panel C presents results for level, slope, and curvature, which are the first three principal components from the cross-section of daily one through five year zero-coupon Treasury bond yields obtained from Gürkaynak et al. (2007). All variables are lagged two day with respect to the FOMC announcement day except for MPU, which is computed as the change from the previous meeting. All explanatory variables are standardized to facilitate comparison. Newey and West (1987) t-statistics are presented in square brackets. The sample period is April 2011 to June 2018.

Bond	1Y	2Y	5Y	7Y	10Y	20Y	30Y
Panel A: Financial market uncertainty							
VIX	−0.01	−0.02	−0.06	−0.06	−0.07	−0.06	−0.06
	[−0.84]	[−1.36]	[−2.81]	[−2.68]	[−2.48]	[−1.90]	[−1.95]
TYVIX	0.04	0.01	0.02	0.01	0.01	−0.01	−0.01
	[2.25]	[0.64]	[0.97]	[0.24]	[0.26]	[−0.34]	[−0.35]
Constant	−0.08	−0.27	−0.35	−0.38	−0.42	−0.44	−0.43
	[−3.85]	[−12.14]	[−12.84]	[−14.56]	[−13.30]	[−12.83]	[−12.46]
R^2(%)	10.68	2.75	13.88	16.51	16.98	18.14	19.93
Panel B: Economic and monetary policy uncertainty							
EPU	−0.01	0.00	−0.02	−0.02	−0.03	−0.04	−0.04
	[−1.15]	[0.28]	[−1.33]	[−1.27]	[−1.44]	[−1.75]	[−1.73]
MPU	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	[−0.97]	[−1.60]	[−1.22]	[−1.10]	[−1.11]	[−0.95]	[−0.98]
Constant	−0.08	−0.27	−0.35	−0.38	−0.42	−0.44	−0.43
	[−3.63]	[−11.87]	[−11.90]	[−13.22]	[−12.22]	[−12.04]	[−11.49]
R^2(%)	2.68	1.45	3.99	4.16	5.15	7.57	7.43
Panel C: Yield curve factors							
Level	−0.04	−0.00	0.05	0.07	0.10	0.11	0.12
	[−4.06]	[−0.13]	[2.19]	[2.88]	[3.68]	[4.58]	[4.51]
Slope	0.07	0.02	0.06	0.05	0.07	0.07	0.07
	[7.88]	[1.50]	[3.52]	[2.85]	[3.23]	[3.50]	[3.37]
Curv	−0.00	−0.04	−0.04	−0.03	−0.03	−0.01	−0.00
	[−0.04]	[−1.33]	[−1.10]	[−1.02]	[−1.00]	[−0.27]	[−0.15]
Constant	−0.08	−0.27	−0.35	−0.38	−0.42	−0.44	−0.43
	[−8.55]	[−16.83]	[−19.32]	[−20.85]	[−22.21]	[−23.76]	[−23.15]
R^2(%)	72.81	36.12	50.32	48.65	59.88	65.72	66.89

market and subsequently selling it in the spot market is given by $RX_{t+1} = (S_{t+1} - F_t)/S_t$, where S_t and F_t denote spot and forward rates, respectively. This is equivalent to the spot exchange rate change minus the forward premium $RX_{t+1} = (S_{t+1} - S_t)/S_t - (F_t - S_t)/S_t$. Since the covered interest parity holds in the data (Akram et al., 2008), forward discounts approximately equal interest rate differentials $(S_t - F_t)/S_t \approx i_t^\star - i_t$, where $i_t^\star$ and i_t represent the foreign and domestic interest rates, respectively, over the maturity of the forward contract. We form three currency portfolios by sorting currencies on the basis of their forward discounts. P1 contains the currencies with the lowest interest rate (funding currencies) and P3 the currencies with the highest interest rates (investment currencies). As in Mueller et al. (2017), we compute daily currency excess returns using daily forward discounts and spot exchange rate changes, assuming that the interest rate differential is earned linearly over the month. Portfolio excess returns are equal-weighted averages of the currency excess returns in each portfolio.

Figure 5 presents our results graphically. As for stocks, there is no discernable relation between currency betas and carry trade returns on non-announcement days, nor are there any particular return differences between funding and investment currencies. There are, however, other noteworthy aspects of the figures. First, investment currencies earn high excess returns on PC days, but low returns on non–PC days. Funding currencies, conversely, earn large excess returns on non–PC days. These observations have implications for currency market risk factors. Lustig et al. (2011) introduce two risk factors from the cross-section of carry trade portfolios: the HML_{FX} factor, which is a zero-cost long-short portfolio that buys (sells) high (low) interest currencies, and the dollar (DOL) factor, which is a simple trading strategy that is short the USD and long foreign currency. Our results imply that both factors earn most of their returns on PC days, whereas they both earn low returns on non–PC days. The empirical observation that the DOL factor earns higher excess returns on PC days is analogous to the general results for stock market returns. We further note that the effects are stronger for investment currencies on PC days, which is consistent with the FOMC announcement day findings in Mueller et al. (2017).

5. Discussion

Our main findings document (i) that stocks earn large excess returns that are positively related to their betas on PC days, (ii) that the cross-sectional dispersion in betas declines on PC days, and (iii) that stock-bond correlations switch signs on PC days. The findings have implications for both theoretical work aiming at explaining the announcement day premium and empirical work that assesses the influence of monetary policy on asset prices and evaluates possible transmission channels. Specifically, our results suggest that FOMC announcements with and without a PC should be treated separately to accurately assess the influence of monetary policy. Below we discuss possible explanations of our findings.

5.1. Excess stock returns on PC days

Explanations for the high announcement day excess returns usually fall into one of three categories: (i) risk premia (Savor and Wilson, 2013), (ii) market surprises (Cieslak et al., 2019), or (iii) asset pricing puzzles (Lucca and Moench, 2015).

In standard asset pricing theory, excess returns are earned as compensation for undiversifiable risk. The higher excess returns earned by stocks on PC days (which are linearly increasing in their exposure to systematic risk) could therefore be a result of variation in systematic risk across announcement days. For example, if investors believe that the Fed will only reveal price-relevant information (e.g., policy actions, the likely path of interest rates, or new

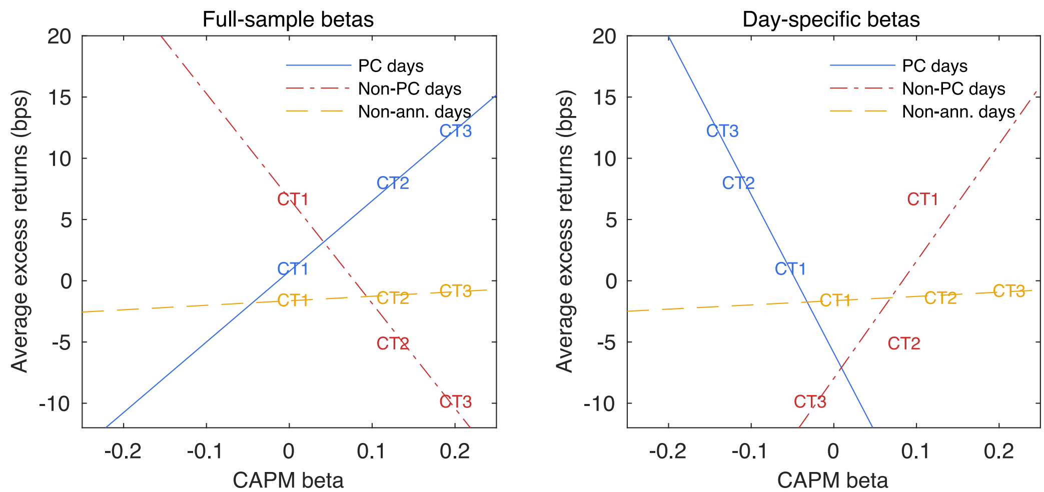

Fig. 5. Average excess currency portfolio returns. This figure plots average daily excess returns in basis points (bps) against full sample portfolio betas (left panel) and day-specific portfolio betas (right panel) along with implied estimates of the Security Market Lines for three currency carry trade portfolios sorted on forward discounts separately for announcement days with a press conference (PC days, blue entries and solid line), announcement days without a PC (non–PC days, red entries and dash-dotted line), and non-announcement days (yellow entries and dashed line). The sample period is April 2011 to June 2018. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

macroeconomic outlooks) on PC days, then systematic and political (Pástor and Veronesi, 2013) risk is likely to be higher on PC days. In a nutshell, the risk on these days is high because investors might learn that the macroeconomy is performing worse than expected (Savor and Wilson, 2013; Wachter and Zhu, 2021). This explanation relies on two key attributes. First, investors believe that it is more likely that the FOMC will provide price-relevant information on PC days. Second, the Fed itself starts to delay price-relevant information to meetings with a PC. Boguth et al. (2019) document that investor attention has shifted to PC days and that market participants view these meetings as more important. Such a shift in investor attention can itself influence the behavior of the Fed as investor attention is critical to the transmission of monetary policy (Stein, 1989). This is particularly true when the Fed is averse to surprising market participants (Stein and Sunderam, 2018; Cieslak et al., 2019).[19] This may in turn influence market expectations as attention and the likelihood of price-relevant information arrivals shift to PC days. Our empirical findings are therefore consistent with the idea that investor attention influences the magnitude of the announcement risk premium. Models of this kind can be found in Sims (2013), Abel et al. (2007, 2013), Andrei and Hasler (2015), Kacperczyk et al. (2016), Huang and Liu (2007), and Ben-Rephael et al. (2021). Fisher et al. (2020) present empirical evidence that rising attention prior to macroeconomic announcements is associated with higher risk premia and lower uncertainty. We find that the excess returns to risky asset are higher on PC days and that uncertainty drops on PC days, which is consistent with an attention channel. Moreover, the results are also consistent with models of disagreements and resolution of uncertainty (Hong and Stein, 2007; Ai and Bansal, 2018; Bollerslev et al., 2018; Bauer et al., 2020).

We cannot rule out that the higher stock returns on PC days originate from other sources. For example, changing market expectations about how and when the Fed undertakes monetary policy actions is a possible driver of the differential reactions to announcements with and without a PC that we document in this paper. The FOMC announced and conducted most monetary policy actions (conventional and unconventional) on meetings with a PC, which complicates a full separation of PCs and the information released during the meetings. However, PCs are known in advance and therefore provide a useful ex ante distinction that captures the return differences well. The high stock returns on PC days may also originate from good news, positive surprises, or resolution of uncertainty. In that case, the returns are more likely to represent return realizations rather than risk premia.

5.2. Time-varying portfolio betas and cross-sectional beta dispersion

The higher excess stock returns earned on PC days together with the observed decline in the cross-sectional dispersion of portfolio betas provide a challenge for dynamic risk models (Patton and Verardo, 2012; Savor and Wilson, 2016) and existing models of the announcement day premium that assume invariant portfolio betas across announcement days (e.g., Wachter and Zhu (2021)). The reduction in the cross-sectional dispersion of portfolio betas does, however, suggest that stocks become more similar in terms of their exposure to systematic market risk on PC days. Such behavior can be generated within several frameworks. First, for beta-sorted portfolios, Proposition 4 in Frazzini and Pedersen (2014) suggests that betas should compress with new information about wealth or margin requirements. Second, Andrei et al. (2020) propose a framework in which an informational distortion leads to underestimation (overestimation) of low-risk (high-risk) betas on days with no announcements. Third, Andersen et al. (2020) show that the intraday dispersion pattern of betas for the constituents of the S&P500 index declines over the trading day and, like us, that they compress more sharply around FOMC announcements due to information flows (but do not distinguish between PC and non–PC days). However, none of the above frameworks provide a mechanism for understanding the large differences in excess returns across PC and non–PC days and the associated differences in the shape of the SML. For example, the observation that the cross-sectional dispersion declines while all portfolios earn higher excess returns seems hard to unify within a standard asset pricing framework. The higher returns for portfolios with increasing betas are consistent with the idea embedded in dynamic risk models, whereas the higher returns for portfolios with declining betas are not. Instead, they would suggest that returns are earned as realizations from drops in risk premia. Adding to the puzzle, we find that bond betas increase

[19] As an example, at the September 2011 meeting, Sandra Pianalto, president of the Cleveland Fed, suggested delaying Operation Twist until the following meeting with reference to the press conference. Transcript is available here: https://www.federalreserve.gov/monetarypolicy/files/FOMC20110921meeting.pdf

on PC days, and even become positive, without affecting bond excess returns markedly. Savor and Wilson (2013) and Wachter and Zhu (2021) similarly demonstrate that bond betas increase dramatically on announcement days, but we find that this effect is now limited to PC days. Overall, we conclude that dynamic risk models are unlikely to explain our findings.

5.3. Time-varying and sign-switching stock-bond correlations

The changing stock-bond correlations that we uncover also provides a challenge to the asset pricing literature. While Eraker (2008), Bekaert et al. (2010), and Bansal and Shaliastovich (2013) analyze stocks and bonds jointly, and allow for a time-varying stock-bond correlation, the variation does not permit sign switches. Ermolov (2018), Kozak (2019), and Campbell et al. (2020) provide first attempts at macroeconomic models with time-varying and sign-switching stock-bond correlations. Ermolov (2018) and Campbell et al. (2020) use an external habit specification to achieve time-varying stock-bond correlations, whereas Kozak (2019) formulates a production-based model with Epstein and Zin (1989) preferences and two physical technologies that gives rise to a hedging premium and a risk premium. Cieslak and Pang (2020) offer a similar explanation by decomposing the overall stock and bond price response into components related to monetary news, growth news, and two distinct shocks generating time-varying risk premiums: a common risk premium and a hedging risk premium. The important contribution is that common and hedging premium shocks affect stocks and bonds differently so that the relative importance can generate time-varying and sign-switching stock-bond correlations. Our empirical results provide some support for these models.

Our empirical findings for the dynamics of Treasury bonds and their correlation with stocks is further consistent with a "*flight-to-safety*"-type mechanism. Baele et al. (2020) propose a definition of a flight-to-safety day that resembles non–PC days in that bond excess returns are positive, stock market excess returns and stock-bond correlations are negative, and uncertainty remains unsolved. Caballero and Krishnamurthy (2008) offer a mechanism for flight-to-safety based on liquidity shortages and Knightian uncertainty (Knight, 1921). When liquidity is limited, the agent fears being caught in a shortage and sells stocks in favor of bonds. This gives rise to a flight-to-safety episode. To the extent that Knightian uncertainty is higher on non–PC days, our empirical findings support the predictions of Caballero and Krishnamurthy (2008) and the high returns can be interpreted as originating from hedging demand. Flight-to-safety and stock-bond reallocations could also originate from changes to investors' risk aversion on FOMC announcement days (Bekaert et al., 2013; Kroencke et al., 2021). Adrian and Shin (2010) provide a possible channel in which risk aversion is influenced by changes to the balance sheets of financial intermediaries. He and Krishnamurthy (2013), Adrian et al. (2014), and He et al. (2017) all study the impact of financial intermediaries. Adrian et al. (2019) provide further support by documenting a nonlinear relation between stock and bond returns and VIX that affects stocks and bonds asymmetrically and cause flight-to-safety episodes when VIX increases from moderate to high levels. Last, to the extent that the communication differs across non–PC and PC days, our results could also be driven by the results in Cieslak and Schrimpf (2019) who show that stock-bond correlations respond differently to news about monetary policy, economic growth, and financial risk premia.

6. Concluding remarks

This paper shows that distinguishing between scheduled FOMC announcements with and without a PC is important for accurately assessing the asset pricing implications of monetary policy announcements. Our empirical findings suggest that stocks earn high excess returns on PC days that are strongly and positively related to their betas as predicted by the CAPM, whereas excess stock returns are negligible and unrelated to their betas on non–PC days. The stronger relation between expected returns and betas on PC days is partially caused by a reduction in the cross-sectional dispersion of portfolio betas that steepens the slope of the SML. This compression is detected using both daily and intraday return data. Treasury bonds, conversely, earns statistically indistinguishable returns on PC and non–PC days, but experience sign-switches in bond betas and stock-bond correlations on PC days where they turn positive. We show that stock-bond correlations on FOMC announcement days are closely related to values of VIX, TYVIX, and the level and slope of the term structure prior to the meeting. Last, we show that our empirical results regarding higher returns to risky asset on PC days extend to a sample of international currencies sorted on the basis of their forward discount. In sum, we find that asset prices respond differently to scheduled FOMC announcements with and without a PC.

Declaration of Competing Interest

No.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jbankfin.2021.106163.

CRediT authorship contribution statement

Simon Bodilsen: Conceptualization, Methodology, Software, Formal analysis, Writing - review & editing. **Jonas N. Eriksen:** Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Niels S. Grønborg:** Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing.

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