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Inferring Stock Duration Around FOMC Surprises: Estimates and Implications

Zhanhui Chen
Hong Kong University of Science and Technology, Department of Finance
chenzhanhui@ust.hk

Abstract

Discount rates affect stock prices directly via the discount-rate channel or indirectly via the cash-flow channel because expected future cash-flow growth varies with the discount rate. The traditional Macaulay duration captures the effect from the discount-rate channel. I propose a novel duration measure, the effective equity duration, to capture the effects from both channels. I estimate it around unexpected policies in the federal funds rates. I find that the equity yield curve is hump-shaped because expected future cash-flow growth increases with the discount rate. The effective equity duration captures information other than monetary policy risk.

I. Introduction

Discount rates influence stock prices directly via the discount-rate channel (stock prices drop when discount rates increase) or indirectly via the cash-flow channel because expected future cash-flow growth often covaries with the discount rate. The traditional Macaulay duration captures the direct effect of discount rates on stock prices via the discount-rate channel. In other words, the Macaulay duration assumes that future cash-flow growth does not vary with the discount rate. The Macaulay duration is an appropriate measure if one cares only about the timing of future cash flow or for assets with fixed future cash flow (e.g., bonds).[1] However, for stocks, the expected future cash-flow growth often increases with the discount rate (see, e.g., Menzly, Santos, and Veronesi (2004), Lettau and Ludvigson (2005),

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[1]The Macaulay duration is widely used. For example, previous articles use it to explain the size, value, profitability, investment, low-beta, high-payout, long-term-reversal, momentum, and low-idiosyncratic-volatility premiums (Da (2009), Chen and Yang (2019), Chen and Li (2019), Gonçalves (2021b), and Gormsen and Lazarus (2019)).

and Binsbergen and Koijen (2010)). Therefore, the indirect effect of discount rates on stock prices via the cash-flow channel becomes important. This requires a new duration measure to capture the overall effects, including both direct and indirect effects. This article proposes such a measure: the effective equity duration. This duration measure is useful for portfolio-choice or risk-management purposes (see, e.g., Hasler, Khapko, and Marfè (2019)). For example, recessions are often accompanied by discount-rate shocks. The discount rate and expected future cash-flow growth usually increase, whereas stock prices drop. This poses a price risk to stocks and portfolios. Different stocks exhibit different price sensitivities to discount-rate shocks. The effective equity duration tells us the overall impact of the discount rate on stock prices and helps us manage portfolio risks when facing discount-rate shocks.

The effective equity duration is defined as the negative ratio of the percentage change in stock prices to changes in the discount rate. The effective equity duration can be viewed as the Macaulay duration adjusted by the comovement between the discount rate and the expected future cash-flow growth. Previous articles usually use fundamental cash-flow information to estimate the Macaulay duration for stocks. However, the future cash flows and discount rates of stocks are usually unknown, which makes such estimation difficult. This article proposes an event-based estimation of the effective equity duration that uses price information. Tapping into the recent literature examining the impact of monetary policy on stock prices (see, e.g., Bernanke and Kuttner (2005), Ozdagli (2018), Jiang and Sun (2019), Neuhierl and Weber (2019), and Ozdagli and Velikov (2020)), I use policy surprises regarding the federal funds rate set by the Federal Open Market Committee (FOMC) as the events ("FOMC surprises" hereafter). I use the Federal Funds futures traded at the Chicago Mercantile Exchange (CME) to measure the federal funds rate expected by the markets and to detect the policy surprises after FOMC announcements. The use of FOMC surprises provides several advantages. First, FOMC surprises affect expected stock returns in a nontrivial way. Second, FOMC surprises affect all stocks simultaneously. This avoids nonsynchronous issues across stocks, which can occur when using other information (e.g., accounting data). Third, we have market-based measures of FOMC surprises via CME Federal Funds futures, whereas most other events lack such measures. Fourth, most FOMC decisions are announced during regular trading hours, which allows us to use high-frequency trading data to precisely measure the stock price reactions.

The effective equity duration is estimated in 4 steps. First, following Ozdagli (2018), Neuhierl and Weber (2019), and Ozdagli and Velikov (2020), I use an event window of 60 minutes before and 5 minutes after the FOMC announcements and use CME Federal Funds futures to derive the FOMC surprises. Second, I choose an event window of 30 minutes before and 10 minutes after the announcements and use New York Stock Exchange (NYSE) Trade and Quote (TAQ) data to compute the stock price reactions. Third, I use a vector autoregressive (VAR) model to compute changes in the expected returns of the market portfolio and apply the capital asset pricing model (CAPM) to compute the changes in the discount rates for individual stocks. VAR models are widely used in predictions (Campbell and Vuolteenaho (2004), Campbell, Polk, and Vuolteenaho (2010), Engsted, Pedersen, and Tanggaard (2012), Chen, Da, and Larrain (2016), and Campbell, Giglio, Polk, and Turley (2018)). The performance of the CAPM on macro-announcement days has been confirmed by Savor and Wilson (2014) and Ai, Bansal, Im, and Ying (2018). Finally, the effective equity duration can be computed as the negative ratio of the percentage change in the stock prices to the changes in the discount rate. For comparison, I also compute the Dechow, Sloan, and Soliman (2004) duration, which is the Macaulay duration.

The final sample includes 47 FOMC announcements selected from 1995 to 2016. The effective equity duration has a mean of 41.22 years. This is close to the mean price–dividend ratio of the S&P 500 from 1963 to 2015, which is 37.46. In contrast, the Dechow et al. (2004) duration has a mean of 15.96 years. Next, I construct 10 duration-sorted portfolios. The average monthly portfolio return increases from 1.05% in portfolio 1 to 2.28% in portfolio 4 and then decreases to 0.01% in portfolio 10. That is, the equity yield curve is hump-shaped. Overall, long-duration stocks have lower returns, and the duration effect lasts up to 30 months. Portfolio alphas computed from various models exhibit similar patterns. In contrast, portfolios sorted by the Dechow et al. duration exhibit a downward-sloping yield curve. The hump-shaped yield curve of the effective equity duration arises from the comovement between the discount rate and future cash-flow growth. An increase in the discount rate has two opposite effects on stock duration. Generally, when the discount rate increases, the Macaulay duration and the effective equity duration both decrease, suggesting a downward-sloping yield curve. However, because the future cash-flow growth increases with the discount rate, cash flows in the far distant future become larger and more important. This increases the effective equity duration and generates an upward-sloping yield curve. The joint effects give the yield curve a hump shape.

I also explore the risks that may be captured by duration. First, I investigate the effects of some firm characteristics on duration. Consistent with Chen and Li (2019), Gonçalves (2021b), and Gormsen and Lazarus (2019), I find that value and profitable stocks generally have a shorter duration. However, examining the subsamples of short-duration and long-duration stocks, I find that gross profitability increases with duration among short-duration stocks, whereas book-to-market equity has a negative correlation with duration among long-duration stocks. This may shed some light on why the value premium appears to hedge against the profitability premium (Novy-Marx (2013), Wahal (2019)). Second, I examine whether duration captures the risk of monetary policy exposure (MPE). Ozdagli and Velikov (2020) show that high-MPE stocks have lower future returns. I find that MPE and the effective equity duration have a negligible correlation, and the MPE effect and duration effect both exist after controlling for each other. This suggests that the effective equity duration captures some information other than the MPE.

One might worry about the potential measurement errors of duration estimation. First, high-frequency data inevitably contain some microstructure noise. Second, daily VAR estimates might be less accurate. I address these concerns in two ways. First, I use placebo tests to rule out the concern about microstructure noise. Specifically, I select the same weekday 4 weeks before and after FOMC announcements as the placebo test dates. I use the same time window as the FOMC event window and follow the same procedures to estimate the effective equity duration on these placebo test dates. I find that no systemic stock price reactions occur over the time window on the placebo test dates and that 10 duration-sorted portfolios have indistinguishable returns. Therefore, the main results are not driven by microstructure noise. Second, instead of using the VAR approach, I use the lower and upper bounds of the expected excess market returns provided by Chabi-Yo and Loudis (2020) to estimate changes in the expected market returns. Chabi-Yo and Loudis (2020) use S&P 500 index option prices to infer the bounds of expected excess market return, based on the no-arbitrage condition. I find that estimates of the changes in the expected market returns from the VAR approach and those based on Chabi-Yo and Loudis (2020) follow identical distributions. Moreover, the results based on Chabi-Yo and Loudis (2020) are qualitatively similar to those based on the VAR approach. This validates the results from the VAR approach.

This article complements the recent literature on the estimation of stock duration. To compute the Macaulay duration, previous articles often rely on fundamental cash-flow information. They typically use some statistical models to estimate future cash flows, together with actual earnings/dividend data or analyst forecasts. For example, Da (2009) proposes a cash-flow-based duration measure as an infinite sum of dividend growth rates. Dechow et al. (2004), Weber (2018), and Chen and Li (2019) assume the first-order autoregressive (AR(1)) processes of book equity growth and return on equity (ROE). Gonçalves (2021b) uses a VAR model of 12 state variables to forecast future cash flows. Gormsen and Lazarus (2019) use some firm characteristics to predict duration. Assuming some specific or even common processes of cash flows for stocks might introduce model misspecifications and measurement errors. Moreover, researchers often use exogenously specified discount rates or even a common discount rate for all stocks (see, e.g., Dechow et al.), which makes it less desirable to study cross-sectional return variations.[2] This article proposes the effective equity duration, which considers the effects of discount rates on future cash-flow growth and uses an event-based approach to estimate it. Nevertheless, my approach has several limitations. First, it is limited by data availability (FOMC surprises may not occur every year). Second, it could be affected by microstructure noise associated with high-frequency data. In contrast, prior approaches use accounting data and have a long sample period with less microstructure noise.

This article is related to the large body of literature on the effects of monetary policy on asset prices. More closely related to my work, Ozdagli (2018), Jiang and Sun (2019), and Ozdagli and Velikov (2020) study the interest rate sensitivities of stocks (i.e., the dollar duration). Jiang and Sun study the differential effects of interest rate changes on high- and low-dividend stocks. Ozdagli shows that firms with higher information friction respond weakly to FOMC surprises. Ozdagli and Velikov show that stocks with a greater MPE have lower returns. My article studies stock price sensitivity to changes in discount rates (instead of interest rates) after monetary shocks to estimate the equity duration. I find that the effective equity duration captures information in addition to the monetary policy risk.

[2]As an exception, Gonçalves (2021b) improves on Dechow et al. (2004) by using the present-value identity to endogenously compute the discount rates instead of assuming a constant discount rate for all stocks.

Broadly speaking, this article relates to the empirical literature on the yield curve of risky assets (see, e.g., Binsbergen, Brandt, and Koijen (2012), Binsbergen, Hueskes, Koijen, and Vrugt (2013), Binsbergen and Koijen (2017), Gonçalves (2021a), Giglio, Kelly, and Kozak (2020), and Miller (2020)). My article provides estimates of the effective equity duration for individual stocks to compute the yield curve, whereas most studies use cash-flow information to infer the yield curve. The effective equity duration generates a hump-shaped yield curve, which is unlike the downward-sloping curve typically found with the Macaulay duration.

The rest of the article proceeds as follows: Section II introduces the effective equity duration and discusses how it differs from the Macaulay duration. Section III describes the data and methods used to estimate stock duration. Section IV presents the main results of the duration estimates and the equity yield curve. It also explores how duration is related to firm characteristics and MPE risk. Section V presents the placebo tests and uses alternative estimates of changes in the expected market returns to address concerns regarding measurement errors. Finally, Section VI concludes.

II. Measuring the Effective Equity Duration

A. Defining the Effective Equity Duration[3]

I use the present-value identity to illustrate how to capture the effects of discount rates on stock prices. Consider the price of stock i at time t, $P_{i,t}$, as the summation of discounted future cash flows. That is,

$$P_{i,t} = \mathrm{CF}_{i,t} \sum_{h=1}^{\infty} e^{-h\left(Er_{i,t} - Eg_{i,t}\right)}, \tag{1}$$

where $\mathrm{CF}_{i,t}$ is the cash flow at time t; h indicates time $t+h$; and $Er_{i,t}$ and $Eg_{i,t}$ are the long-term average discount rate and cash-flow growth rate (both are continuously compounded), respectively. Taking the logarithm over both sides, we get

$$p_{i,t} = cf_{i,t} + ln\left[\sum_{h=1}^{\infty} e^{-h\left(Er_{i,t} - Eg_{i,t}\right)}\right] \equiv p\left(Er_{i,t}, Eg_{i,t}, cf_{i,t}\right), \tag{2}$$

where $p_{i,t}$ and $cf_{i,t}$ are the logarithmic values of $P_{i,t}$ and $\mathrm{CF}_{i,t}$, respectively. The present-value relationship in equation (2) says that stock price is a function of the discount rate, expected future cash-flow growth rate, and currently realized cash flows, that is, $p(Er_{i,t}, Eg_{i,t}, cf_{i,t})$.

Taking the total differential of $p(Er_{i,t}, Eg_{i,t}, cf_{i,t})$ gives the following approximation:

$$\Delta p_{i,t} \approx \frac{\partial p_{i,t}}{\partial Er_{i,t}} \Delta Er_{i,t} + \frac{\partial p_{i,t}}{\partial Eg_{i,t}} \Delta Eg_{i,t} + \frac{\partial p_{i,t}}{\partial cf_{i,t}} \Delta cf_{i,t}. \tag{3}$$

[3]I thank Andrei Gonçalves for suggesting this exposition.

Note that in equation (2) $(\partial p_{i,t}/\partial Er_{i,t}) = -(\partial p_{i,t}/\partial \mathrm{E}g_{i,t})$, and $(\partial p_{i,t}/\partial cf_{i,t}) = 1$. Therefore, the sensitivity of the stock price with respect to the discount rate satisfies

(4) $$\frac{\Delta p_{i,t}}{\Delta Er_{i,t}} = \frac{\partial p_{i,t}}{\partial Er_{i,t}}\left(1 - \frac{\Delta Eg_{i,t}}{\Delta Er_{i,t}}\right) + \frac{\Delta cf_{i,t}}{\Delta Er_{i,t}}.$$

Consider some events that influence the expected returns $(Er_{i,t})$ but not the realized cash flows at time t $(cf_{i,t})$ (i.e., $(\Delta cf_{i,t}/\Delta Er_{i,t}) = 0$; these conditions can be easily satisfied). Then the stock price sensitivity to the discount rate is

(5) $$\frac{\Delta p_{i,t}}{\Delta Er_{i,t}} = \frac{\partial p_{i,t}}{\partial Er_{i,t}}\left(1 - \frac{\Delta Eg_{i,t}}{\Delta Er_{i,t}}\right).$$

Thus, the discount rate affects stock prices in two ways. First, it directly influences stock prices via the discount-rate channel (a decrease in discount rate increases stock prices), that is, the partial derivative of the logarithmic stock price with respect to the discount rate, $(\partial p_{i,t}/\partial Er_{i,t})$. Second, because the future cash-flow growth $(Eg_{i,t})$ of risky assets might move with the discount rate, the discount rate indirectly affects stock prices via the future cash-flow growth, that is, the cash-flow channel. The indirect effect is $(\partial p_{i,t}/\partial Eg_{i,t})(\partial Eg_{i,t}/\partial Er_{i,t}) = -(\partial p_{i,t}/\partial Er_{i,t})(\partial Eg_{i,t}/\partial Er_{i,t})$.

Next, let's consider the standard Macaulay duration (D^{Macaulay}), which is defined as the weighted average of future cash-flow timings. That is, for stock i, at time t,

(6) $$D_{i,t}^{\text{Macaulay}} = \sum_{h=1}^{\infty} w_{i,t}^{(h)} \times h,$$

where the weight $w_{i,t}^{(h)} = \left[CF_{i,t} \cdot e^{-h\left(Er_{i,t} - Eg_{i,t}\right)}\right]/P_{i,t}$. From equation (2), we see that

(7) $$D_{i,t}^{\text{Macaulay}} = -\frac{\partial p_{i,t}}{\partial Er_{i,t}}.$$

Therefore, the Macaulay duration captures the partial derivative of the logarithmic stock price with respect to the discount rate, which is the direct effect of the discount rate on stock price.

Substituting equation (7) into equation (5), we see that the total effects of the discount rate on the stock price are related to the stock duration:

(8) $$\frac{\Delta p_{i,t}}{\Delta Er_{i,t}} = -D_{i,t}^{\text{Macaulay}}\left(1 - \frac{\Delta Eg_{i,t}}{\Delta Er_{i,t}}\right).$$

Let's formally define the effective equity duration, $D_{i,t}$, as follows:

(9) $$D_{i,t} \equiv D_{i,t}^{\text{Macaulay}}\left(1 - \frac{\Delta Eg_{i,t}}{\Delta Er_{i,t}}\right) = -\frac{\Delta p_{i,t}}{\Delta Er_{i,t}}.$$

We see that the effective equity duration usually differs from the Macaulay duration. The Macaulay duration captures the direct effect of the discount rate on the stock prices, whereas the effective equity duration captures the total effects (including both direct and indirect effects) of the discount rate on the stock price. The Macaulay duration measures cash-flow timing, but the effective equity duration also concerns the expected cash-flow growth. For stocks, because the expected returns and expected cash-flow growth usually have a positive correlation (Menzly et al. (2004), Lettau and Ludvigson (2005), and Binsbergen and Koijen (2010)) (i.e., $(\Delta Eg_{i,t}/\Delta Er_{i,t}) > 0$), the effective equity duration is smaller than the Macaulay duration. The Macaulay duration is an appropriate measure if cash-flow growth does not vary with the discount rate ($(\Delta Eg_{i,t}/\Delta Er_{i,t}) = 0$). For example, the coupons of bonds are largely fixed if there is no default risk or if one cares only about the timing of future cash flows of risky assets, as in the constant dividend growth model. In this case, $D_{i,t} = D_{i,t}^{\text{Macaulay}}$. However, for risky assets, cash-flow growth often moves with the discount rate. Sometimes one may wish to measure the total effects of discount rates on stock prices, which is important for portfolio-optimization or risk-management purposes. For example, when risk aversion increases during a recession, the expected returns and expected future cash-flow growth usually increase, whereas stock prices drop. However, different stocks have quite different stock price reactions (i.e., different stock price sensitivities to the discount-rate shocks). We often wish to understand the overall impact of discount rates on asset prices to optimize an investment portfolio or manage portfolio risks. This requires us to use the effective equity duration instead of the Macaulay duration. We can use equation (9) to estimate the effective equity duration.

B. Measuring Effective Equity Duration: An Event-Based Approach

To utilize equation (9), consider a discretized version. Suppose that some informational events affect firms' discount rates. For an event on date t and time s, suppose that the discount rate of stock i changes by $\Delta \text{ER}_{i,t}$ (a discrete counterpart of $\Delta Er_{i,t}$) around this event. Then we can compute the effective equity duration as follows:

$$D_{i,t} = -\frac{\frac{\Delta P_{i,t}}{P_{i,t,s-}}}{\Delta \text{ER}_{i,t}}, \tag{10}$$

where $\Delta P_{i,t} \equiv P_{i,t,s+} - P_{i,t,s-}$, and $P_{i,t,s-}$ and $P_{i,t,s+}$ are stock prices before and after the event, respectively. Note that $\Delta \text{ER}_{i,t}$ is usually different from the realized return around the event, which is $(\Delta P_{i,t}/P_{i,t,s-})$.

I choose the unexpected policies in the federal funds rate (i.e., FOMC surprises) over a short window as the events.[4] I use the CME Federal Funds futures to measure the federal funds rate expected by the markets. The changes in Federal Funds futures after FOMC announcements then tell us the FOMC surprises. FOMC surprises include unexpected policy inactions or unexpected policy moves. For example, markets might be surprised on days that the FOMC announces no changes in the federal funds rate if markets previously expected some changes or when the changes announced by FOMC are not fully anticipated by the markets

[4]FOMC announcements might contain news other than federal funds rates, such as news about economic outlook or liquidity provisions, which is not considered in this article because of the lack of a market-based measure of surprise components.

(i.e., different magnitudes or even directions). The use of FOMC surprises provides some benefits. First, I can safely assume that FOMC surprises over a short window do not change the realized cash flows but have nontrivial effects on expected stock returns (i.e., $(\Delta cf_{i,t}/\Delta Er_{i,t}) = 0$ and $\Delta Er_{i,t} \neq 0$). Therefore, I can use the approximation in equations (5) and (10). Second, FOMC surprises provide simultaneous shocks to all stocks, which allows me to measure their duration simultaneously and facilitates cross-sectional comparison. Third, we have market-based measures of the unexpected policies of the federal funds rate via Federal Funds futures traded at the CME. Last, most FOMC decisions are announced during regular trading hours, which allows me to use high-frequency trading data to precisely measure stock price reactions.[5]

III. Estimation: Data and Methods

A. Data

I use the stock price reactions and changes in the discount rate due to unexpected monetary policies to infer the effective equity duration. To minimize the potential noise from other news, I examine the market reactions over a narrow window around FOMC announcement times. First, I collect the exact FOMC announcement timestamps, denoted as time s. Second, I use the tick data of Federal Funds futures purchased from CME to compute the FOMC surprises, that is, the unexpected policy decisions in the federal funds rates. See Appendix A of the Supplementary Material for more details about FOMC announcement times and CME Federal Funds futures data. Third, I use NYSE TAQ data to measure stock price reactions around FOMC surprises. Last, I use daily and monthly CRSP data and annual Compustat data. Because of limitations in the availability of TAQ, FOMC announcements, and CME Federal Funds futures data, the sample period is 1995–2016.

1. FOMC Announcements

By law, the FOMC must meet at least four times per year; since the 1980s, it has often had eight scheduled meetings per year. Before 1994, most monetary policy decisions were not announced to the public, but since Feb. 1994, the decisions from the scheduled meetings have been announced to the public. From Sept. 1994 to May 1999, statements were released only when there was a change in policy. Since May 1999, statements have always been released after the meetings, regardless of whether there was a policy change. The announcement dates and times for scheduled meetings are published in June of the previous year. From Sept. 1994 to Mar. 2011, FOMC statements were released at 2:15PM.[6] Since Apr. 2011, the FOMC chair has also held a press conference after some announcements.

[5]Other macroeconomic, industry, or firm-specific news shocks are less desirable. For example, they are often not simultaneous shocks to all stocks and lack market-based measures of surprises. Some macroeconomic news, such as announcements regarding the Consumer Price Index (CPI), Producer Price Index (PPI), and employment, is usually announced by the U.S. Bureau of Labor Statistics at 8:30AM, which is before regular trading hours. This prevents me from measuring the price reactions precisely.

[6]Unless otherwise noted, the timing refers to U.S. Eastern Time.

Thus, from Apr. 2011 to Jan. 2013, announcements were released at 12:30 PM when a press conference was held, whereas announcements without a press conference were released at 2:15PM. Since Mar. 2013, FOMC announcements have been made at 2:00PM.

Although FOMC announcement times are largely fixed for scheduled meetings, the exact announcement times typically vary by several minutes from the scheduled times. Also, there are some unscheduled FOMC meetings, and their announcement times are not disclosed in advance. To detect the market reactions precisely, I collect the exact FOMC announcement times from various sources, including the FOMC website, Bloomberg, Thomson Reuters, the *Wall Street Journal*, Dow Jones Wire, Associated Press, CNBC, and Datastream. I also cross-verify the announcement times with those reported by Lucca and Moench (2015) and Ozdagli and Weber (2019), together with the trading activities of CME Federal Funds futures.

2. CME Federal Funds Futures

Because financial markets are forward-looking, it is important to isolate unexpected policy decisions from anticipated ones. Following Bernanke and Kuttner (2005), Neuhierl and Weber (2018), Ozdagli (2018), Neuhierl and Weber (2019), and Ozdagli and Velikov (2020), I use the tick data of CME Federal Funds futures to measure the federal funds rate expected by the markets and identify FOMC surprises from the changes in Federal Funds futures after FOMC announcements. The CME Federal Funds futures price is computed as 100 minus the average daily federal funds effective rate in the contract-expiration month.[7] Following Gürkaynak, Sack, and Swanson (2005), I use the Federal Funds futures contract that expires in the same month as the FOMC announcement date if the announcement date follows in the first 3 weeks of that month, and I use the Federal Funds futures contract that expires in the next month if the announcement date follows in the last 7 days of the month. If there is an FOMC announcement on date t, with a time of s, I use an event window of $[s - a_f, s + b_f]$ to compute the federal funds rate surprise. First, to minimize microstructure noise, I use the transaction data of Federal Funds futures over $[s - a_f, s + b_f]$ to compute the simple average federal funds rate implied by the Federal Funds futures prices before and after time s, denoted as $f_{t,s-}$ and $f_{t,s+}$, respectively. Next, I compute the federal funds rate surprise, $\Delta R_{f,t}$, which is adjusted by the number of days passed if necessary, as follows:

$$\Delta R_{f,t} = \frac{U}{U-u}\left(f_{t,s+} - f_{t,s-}\right), \tag{11}$$

where u is the day of this FOMC announcement in a month, and U is the number of days in the month.[8] Because the CME data are in Central Time, to match

[7]For example, a futures contract priced at 98 indicates an average daily federal funds rate of 2% in the contract-expiration month. The daily federal funds rate, computed by the Federal Reserve Bank of New York, is the weighted-average rate of overnight interbank loans. The FOMC did not disclose the federal effective rate target before 1994. In 1995, the FOMC explicitly stated its target level for the federal funds rate.

[8]This implicitly assumes that there is only one FOMC announcement in a month, which is true among the events selected.

the CME data with the stock price data, which are in Eastern Time, I adjust the CME transaction time to Eastern Time by adding 1 hour. To minimize microstructure noise, I require FOMC surprises to be at least 0.2 basis points (bps). This is determined by the tick size of CME Federal Funds futures, which is 0.25 bps for the nearest-month contract and 0.5 bps for all other contracts.

3. Stock Price Reactions

I use the daily and monthly products of the NYSE TAQ data to measure the stock price reactions around FOMC surprises on date t and time s, with an event window of $[s-a_s, s+b_s]$. To minimize the effects of microstructure noise, I use the midpoints of the National Best Bid and Offer (NBBO) prices as the stock prices. The NBBO prices are computed as in Holden and Stacey (2014). First, I compute the simple average stock prices before and after time s for stock i on date t, denoted as $P_{i,t,s-}$ and $P_{i,t,s+}$, respectively. Next, I compute the percentage change of stock price for stock i around this event as

$$\frac{\Delta P_{i,t}}{P_{i,t,s-}} = \frac{P_{i,t,s+} - P_{i,t,s-}}{P_{i,t,s-}}, \tag{12}$$

which is the event return for stock i.

4. Other Data: Stocks, Bonds, and Other Macroeconomic News

I also use the daily and monthly stock prices and returns from CRSP and the annual financial data from Compustat. The sample stocks consist of common stocks (with a share code of 10 and 11) listed on the NYSE/American Stock Exchange (AMEX)/NASDAQ, excluding financial and utility firms (e.g., with an SIC code between 4900 and 5000 or between 6000 and 7000).[9] To minimize microstructure noise, I exclude stocks with market capitalizations below the NYSE size breakpoint of the 20th percentile.

I also use the factor returns obtained from the Fama–French data library. Bond yields, including the yields on Moody's BAA and AAA bonds and the 10-year constant maturity bond, are obtained from the Federal Reserve Bank of St. Louis.

I collect other macroeconomic news announcement times from the U.S. Bureau of Labor Statistics website, including inflation (e.g., CPI and PPI) and employment announcements.

B. Choosing Event Windows

The choice of event window is important to precisely detect market reactions. A long event window includes more trades but also inevitably incorporates news other than the FOMC announcements, which contaminates the results. A narrow event window ensures that the FOMC announcements are the only news. The use of

[9]Rising rates might mean higher profits for banks and insurers because higher rates increase their net interest margin, the spread between the returns on loans and investment and the interest and claims they pay to customers. Utilities, which usually have high dividend yields, are sensitive to interest rates because of the high debt load.

narrow event windows also avoids the endogeneity issues associated with monetary policies and stock prices,[10] but it may suffer from microstructure noise. For example, it is well known that the markets become quiet (i.e., there is low trading volume) right before the scheduled macroeconomic news announcements. I explore the trading activities in both CME Federal Funds futures and the stock markets to decide the event windows. I investigate the distribution of the closest trades around the FOMC announcement times. For CME Federal Funds futures, the 75th (90th) percentile of the last trade before the announcements is 23 (125) minutes, and the 75th (90th) percentile of the first trade after the announcements is 4 (35) minutes. For stock markets, the 75th (90th) percentile of the last trade before the announcements is 11 (76) minutes, and the 75th (90th) percentile of the first trade after the announcements is 5 (33) minutes. Based on these distributions, for a given FOMC announcement at time s, I specify the event window for CME Federal Funds futures as $[s-60, s+5]$ and the event window for stock price reactions as $[s-30, s+10]$, with a unit of a minute. This differs from Gürkaynak et al. (2005) and Gorodnichenko and Weber (2016), who choose 30 or 60 minutes around the events. I choose the event window for CME Federal Funds futures to begin earlier and end earlier than the event window for the stock prices to ensure that the information in the Federal Funds futures market is available to the stock markets. Also, because markets react quickly to FOMC surprises, I intentionally choose a short period after the announcements: only 5 minutes for the CME Federal Funds futures and 10 minutes for stocks. Choosing different event windows for CME Federal Funds futures and stocks might cause nonsynchronous issues. Therefore, as a robustness check, I also consider the same event window of $[s-30, s+10]$ for both FOMC surprises and stock price reactions. To avoid possible timing errors, data on the exact minute of FOMC announcements are not used in the analyses.

C. Estimating Effective Equity Duration

I need to estimate stock price reactions and changes in the discount rate to compute the stock duration in equation (10). Clearly, I can directly obtain the percentage change in the stock prices $((\Delta P_{i,t}/P_{i,t,s-}))$ around the event from the TAQ data. Still, I must estimate the change in the discount rate for stock i, $\Delta \mathrm{ER}_{i,t}$, around an event. Savor and Wilson (2014) show that the CAPM performs very well during macroeconomic news announcement days, which is further confirmed by Ai et al. (2018). Therefore, the change in the discount rate for stock i during date t can be computed from the CAPM, as follows:

$$\Delta \mathrm{ER}_{i,t} = \beta_{i,t}\Delta \mathrm{ER}_{M,t} + \left(1-\beta_{i,t}\right)\Delta R_{f,t}, \tag{13}$$

where $\beta_{i,t}$ is the market beta of stock i on date t, and $\Delta \mathrm{ER}_{M,t}$ and $\Delta R_{f,t}$ are changes in the expected market return and the risk-free rate around the event,

[10]For example, it is possible that monetary policies react to the stock markets, or both monetary policies and stock prices respond to some common economic fundamentals. The use of intraday data within a narrow event window alleviates such endogeneity concerns.

respectively.[11] $\Delta R_{f,t}$ is computed from equation (11).[12] Then the effective equity duration can be computed as

$$D_{i,t} = -\frac{\frac{\Delta P_{i,t}}{P_{i,t,s-}}}{\beta_{i,t}\Delta \mathrm{ER}_{M,t} + \left(1-\beta_{i,t}\right)\Delta R_{f,t}}. \tag{14}$$

Because $\Delta R_{f,t}$ is often very tiny, equation (14) says the difference in betas, in addition to the difference in event returns, drives the cross-sectional variations in duration. For example, high-beta stocks have a low duration.

Following Fama and French (1992) and Savor and Wilson (2014), I estimate the market betas of individual stocks in three steps to reduce the estimation errors. First, I use the daily returns over the past year (ending on date $t-1$) to estimate β at date t for each stock. Second, because β estimation is more precise for portfolios, I estimate portfolio βs. I sort all stocks into 100 portfolios based on their individual βs estimated in the first step.[13] I then compute the value-weighted portfolio returns over the past year (ending on date $t-1$) and reestimate the betas for these 100 portfolios, using the daily portfolio returns over the past year. Third, I assign the portfolio beta to individual stocks within a portfolio as their βs.

Next, following Campbell (1991), Campbell and Vuolteenaho (2004), Campbell et al. (2010), Chen et al. (2016), and Campbell et al. (2018), I use VAR to measure changes in the expected market return ($\Delta \mathrm{ER}_{M,t}$). Assume that the economy can be described by a first-order VAR model:

$$z_t = a + \Gamma z_{t-1} + u_t, \tag{15}$$

where z_t is an m-by-1 state vector with the market return $R_{M,t}$ as the first element, a is an m-by-1 vector, Γ is an m-by-m matrix of parameters, and u_t is an m-by-1 vector of shocks that are identically and independently distributed. I can compute the expected market return as the 1-period-ahead forecast from the VAR model. The change in the expected market return, $\Delta \mathrm{ER}_{M,t}$, can then be computed as its difference over time.

The choice of state variables to be included in the VAR system is important when implementing the VAR method. For example, Chen and Zhao (2009) suggest that VAR decomposition is often sensitive to the VAR specifications. However, there is less concern in this article because this article uses VAR to predict future returns instead of return decompositions. Moreover, Engsted et al. (2012) validate the VAR approach and discuss several drawbacks in Chen and Zhao (2009). Engsted et al. (2012) suggest that it is crucial to include the dividend yield to construct a proper VAR system.[14] Following Campbell and Vuolteenaho (2004),

[11] Admittedly, as in Savor and Wilson (2014), this implicitly assumes that market betas do not change over the events.

[12] Note that although CME futures give me risk-neutral estimates, these estimates are similar to the expectations under physical measures for the risk-free rate.

[13] The results are qualitatively similar if they form 50 or 150 portfolios.

[14] Both Chen and Zhao (2009) and Engsted et al. (2012) show that it is insufficient to include the price–earnings ratio in the VAR system. Cochrane (2008) and Campbell et al. (2010) discuss the conditions under which VAR results are robust. Campbell et al. also provide sensitivity analyses to validate the effectiveness of the VAR approach.

Campbell et al. (2010), Engsted et al. (2012), and Campbell et al. (2018), I include 5 state variables in the VAR system. The first variable is the market return. The second variable is the dividend yield of the market portfolio. I use the with- and without-dividend returns of the aggregate market portfolio from CRSP to compute the dividend yield. The third variable is the term spread (TERM), which is computed as the difference between the yield on the 10-year constant maturity bond and the yield on the 3-month Treasury bill. The fourth variable is the default spread (DEF), which is computed as the difference between the yield on Moody's BAA and AAA bonds. The fifth variable is the value spread, which is the value factor (HML) from the Fama–French data library. These variables are known to track the expected returns of the market portfolio. Limited by the data availability of these variables, I estimate the VAR system at a daily frequency, with an extending window. This implicitly assumes that FOMC announcements are the major news that affects the aggregate market movements on those announcement days. As a robustness check, I also consider a sample that excludes the days when other macroeconomic news announcements (e.g., CPI, PPI, and employment news) are made, as reported in Appendix E of the Supplementary Material. The sample period is from 1990 to 2016, and the first estimate begins in 1995.

Lastly, because stock price reactions are estimated over the event window of $[s-30, s+10]$ (i.e., 40 minutes only) for an announcement made at time s, whereas the change in the discount rate is estimated with daily data, I must adjust the duration estimates accordingly. Because there are 390 minutes of trading hours per day (e.g., from 9:30AM to 4:00PM), the effective equity duration is adjusted as follows:

(16) $$D_{i,t} = -\frac{390}{40}\frac{\frac{\Delta P_{i,t}}{P_{i,t,s-}}}{\Delta \text{ER}_{i,t}} = -9.75\frac{\frac{\Delta P_{i,t}}{P_{i,t,s-}}}{\beta_{i,t}\Delta \text{ER}_{M,t} + \left(1-\beta_{i,t}\right)\Delta R_{f,t}}.$$

D. Alternative Duration Measure: Dechow et al.

Dechow et al. (2004) suggest a Macaulay type of duration for stocks. Weber (2018) applies this to study the cross-sectional implications of stock duration. For comparison purposes, I replicate their measure. Following Dechow et al., the modified duration (D^{DSS}) for a stock i can be computed as the weighted-average timing of future cash flows, as follows:

$$D_i^{\text{DSS}} = \frac{\sum_{j=1}^{\infty} j \cdot \text{CF}_{i,j}/(1+\text{ER}_i)^j}{\text{ME}_i(1+\text{ER}_i)},$$

where ME_i is the market equity of stock i at time 0, $\text{CF}_{i,j}$ is the net cash flow to equity holders at time j, and ER_i is the expected return of stock i. As in Dechow et al. (2004), the discount rate ER_i is assumed to be 12% per year for all stocks. To simplify, Dechow et al. (2004) assume that we can forecast the stream of cash flows up to horizon J, and the remaining cash flows beyond J are to be a perpetuity. Thus,

(17) $$D_i^{\text{DSS}} = \frac{\sum_{j=1}^{J} j \cdot \text{CF}_{i,j}/(1+\text{ER}_i)^j}{\text{ME}_i(1+\text{ER}_i)} + \left(J + \frac{1+\text{ER}_i}{\text{ER}_i}\right) \cdot \frac{\sum_{j=J+1}^{\infty} \text{CF}_{i,j}/(1+\text{ER}_i)^j}{\text{ME}_i(1+\text{ER}_i)}.$$

To estimate the duration, I must forecast cash flows for the immediate J periods. Cash flows are computed from the accounting identity $\mathrm{BE}_{i,j} = \mathrm{BE}_{i,j-1} + \mathrm{E}_{i,j} - \mathrm{CF}_{i,j}$, where $\mathrm{BE}_{i,j}$ is the book equity at time j, and $E_{i,j}$ is the earnings in the same period. Earnings can be computed from book equity and ROE. Dechow et al. (2004) assume that book equity grows at the rate of sales growth (SGR). They further assume that SGR and ROE follow two separate AR(1) processes. I project the cash flows for the next T = 10 years and then compute the duration from equation (17) (see Appendix B of the Supplementary Material for details). To allow for better estimates, I use a sample period from 1972 to 2016 to estimate the Dechow et al. duration.

IV. Main Results

A. Descriptive Statistics

Panel A in Table 1 provides an overview of the FOMC announcements from 1995 to 2016. In total, 195 announcements are made; 183 are scheduled in the previous year, and 12 are not previously scheduled. Additionally, 181 announcements are made during the regular trading hours of the stock markets. Fifty-six FOMC announcements include changes in the target federal funds rate. Eight announcements are associated with changes in the monetary policy path (e.g., switching between expansionary and contractionary policies). Twenty-two announcements come with other macroeconomic news announcements (e.g., CPI, PPI, and employment news) on the same day, and 26 announcements are made during National Bureau of Economic Research (NBER) recession months.

Forty-seven FOMC announcements are finally selected, and all are announced during trading hours (see the full list in Table A.1 of the Supplementary Material). One of these events is not previously scheduled. Twenty-three events are associated with unexpected changes in the federal funds rate, and in the other 24 events, the markets are surprised to see no change in the federal funds rate after the FOMC meeting.

Panel B of Table 1 presents some statistics regarding the events. Inspecting these 47 events, we see that the median change in the federal funds rate is 0, with a mean of –2.13 bps. The largest rate cut is 50 bps, as is the largest rate increase. Turning to the FOMC surprises ($\Delta R_{f,t}$), we see that the median surprise is –0.72 bps, and the mean surprise is –2.53 bps. The largest negative surprise is –28.42 bps, and the largest positive surprise is 8.25 bps. Inspecting the stock market reactions, we see that individual stocks have an average return of 21.02 bps around the events. The expected market return decreases by 36.62 bps, and the expected returns of individual stocks decrease by 48.64 bps on average.

Panel B of Table 1 also summarizes some firm characteristics, including the effective equity duration (D), the Dechow et al. (2004) duration (D^{DSS}), the book-to-market equity (B/M), the gross profitability (PROFITABILITY), and the market beta (β). B/M is computed as by Fama and French (1992), and profitability is computed as by Novy-Marx (2013). To avoid outliers, firm characteristics are winsorized at the 1st and 99th percentiles, and both duration measures are trimmed at 1 and 300 years. D has a mean of 41.22 years, and it is very dispersively

TABLE 1

FOMC Announcements and Market Reactions: Descriptive Statistics

Panel A of Table 1 summarizes all Federal Open Market Committee (FOMC) announcements and the selected announcements used in the subsequent analyses. Each FOMC announcement is further categorized based on whether it is scheduled or unscheduled, whether it is disclosed during trading or nontrading hours, whether it comes with changes in the federal funds rate (FFR), whether it comes with changes in the monetary policy path, whether it comes with other macroeconomic news announcements on the same date, and whether it is made in a National Bureau of Economic Research (NBER) recession month. Panel B reports the sample distribution, including the mean, median, standard deviation, and other percentiles of the key variables. It includes actual changes in the FFR, unexpected changes in the FFR ($\Delta R_{f,s}$), event returns of individual stocks ($\Delta P/P$), changes in the expected market returns (ΔER_M), and changes in the expected returns of individual stocks (ΔER), reported in basis points (bps). It also reports other firm characteristics, including the effective equity duration (D), the Dechow et al. (2004) duration (D^{DSS}), the book-to-market equity (B/M), the gross profitability (PROFITABILITY), and the market beta (β). B/M is computed as in Fama and French (1992), and profitability is computed as in Novy-Marx (2013). Panel C reports the autocorrelations and correlations of those firm characteristics. AR(1) denotes the first-order autocorrelation of each series. The sample period is 1995–2016.

Panel A. FOMC Announcements

	Total	Scheduled	Unscheduled	Trading Hours	Nontrading Hours	FFR Changes	Changes in Policy Path	Other Macroeconomic News	NBER Recession
All announcements	195	183	12	181	14	56	8	22	26
Selected announcements	47	46	1	47	0	23	4	4	8

Panel B. Descriptive Statistics

	Mean	Median	Std. Dev.	Minimum	P25	P75	Maximum
News of FFR							
FFR changes (bps)	−2.13	0.00	25.98	−50	0	25	50
FFR surprise ($\Delta R_{f,s}$, bps)	−2.53	−0.72	7.09	−28.42	−4.26	0.68	8.25
Stock market reactions							
Event returns ($\Delta P/P$, bps)	21.02	14.49	89.29	−853.34	−16.14	47.52	1,857.47
ΔER_M (bps)	−36.62	−23.09	147.83	−646.54	−57.51	28.11	464.97
ΔER (bps)	−48.64	−21.03	213.25	−2,061.90	−78.63	15.12	1,531.90
Firm characteristics							
D (years)	41.22	18.14	55.77	1.00	6.78	49.23	299.78
D^{DSS} (years)	15.96	15.39	7.84	1.05	14.34	16.38	297.12
B/M	0.53	0.42	0.43	0.01	0.25	0.68	3.63
PROFITABILITY	0.33	0.30	0.24	−0.71	0.19	0.45	1.32
β	1.07	1.00	0.78	−2.83	0.60	1.48	4.51

Panel C. Autocorrelations and Correlations

	AR(1)	D	D^{DSS}	B/M	PROFITABILITY	β
D	0.54	1.00	0.01	0.05	0.03	−0.17
D^{DSS}	0.99		1.00	−0.19	0.06	0.06
B/M	0.94			1.00	−0.22	−0.05
PROFITABILITY	0.94				1.00	−0.04
β	0.88					1.00

distributed, with a median of 18.14 years and a large standard deviation of 55.77 years. The mean duration is similar to the mean price–dividend ratio of the S&P 500 over 1963–2015, which is 37.46.[15] D^{DSS} is more clustered around its mean (15.96 years), with a small standard deviation of 7.84 years. D^{DSS} has a median estimate similar to that of D, which is 15.39 years. Overall, individual stocks have an average book-to-market equity ratio of 0.53, an average gross profitability ratio of 0.33, and an average beta of 1.07. Panel C of Table 1 shows that D and D^{DSS} have a negligible correlation because D^{DSS} is highly persistent, with an AR(1) coefficient of 0.99, whereas this value is only 0.54 for D. The book-to-market equity ratio is weakly positively correlated with D but strongly negatively correlated with D^{DSS} (with a correlation coefficient of –0.19). Profitability appears to be weakly positively correlated with both D and D^{DSS}. As in Novy-Marx (2013) and Wahal (2019), gross profitability is negatively correlated with B/M (with a correlation of –0.22). Last, D is negatively correlated with market β (a correlation coefficient of –0.17), which is consistent with equation (14). However, the Dechow et al. (2004) duration is weakly positively correlated with market β (a correlation coefficient of 0.06).

Comparing D and D^{DSS}, we see that D has a much larger mean and is more dispersed and less persistent than D^{DSS}. The reasons are follows: First, D^{DSS} assumes AR(1) processes for ROE growth and book equity growth for the first 10 years and a perpetuity after that, which introduces a downward bias in duration estimates. In fact, using a more general VAR system to estimate cash flows and a present-value identity to estimate the discount rates, Gonçalves (2021b) documents a large duration (e.g., a median duration of 40.7 years). Similarly, by improving Dechow et al. (2004) estimation by including more accounting variables to predict ROE and book equity growth, Chen and Li (2019) report a mean duration of 28.66 years. My estimates are also similar to Da (2009) cash-flow duration (Schröder and Esterer (2016) report a mean of 40.34 years). Second, the high autocorrelation of D^{DSS} results from the persistent AR(1) processes assumed in its estimation, whereas D is less persistent because its estimation uses market prices, which fluctuate greatly over time. Also using stock prices to estimate the discount rates, Gonçalves (2021b) finds large duration variations (e.g., the 10th and 90th percentiles are 17.9 and 99.6 years, respectively). Using a VAR system, Chen and Li (2019) report the 25th and 75th duration percentiles of 24.45 and 43.20 years, respectively. Overall, my estimates are more in line with those reported by Gonçalves and Chen and Li.

B. The Equity Yield Curve Implied by the Effective Equity Duration

Similar to the bond yield curve, the equity yield curve reveals the term structure of risky returns in the economy. Most articles find a downward-sloping curve for risky assets, especially during recessions (e.g., S&P 500 index dividend strips, dividend futures, housing markets, volatility markets, currencies, and

[15]This is computed from Robert Shiller's data, available at http://www.econ.yale.edu/~shiller/data/chapt26.xlsx.

government bonds).[16] Weber (2018) and Giglio et al. (2020) show a downward-sloping curve for stock returns. Analogically, what is the equity yield curve implied by the effective equity duration?

I sort all stocks into 10 portfolios based on their effective equity duration estimated in the last month. I then compute the average firm size, the value-weighted portfolio duration, monthly returns, and alphas from various benchmark models, presented in Table 2. First, Panel A shows that the portfolio duration varies considerably, increasing from 3.39 years in portfolio 1 to 114.96 years in portfolio 10. Roughly speaking, the firm size increases over the first 6 portfolios and then decreases over the next 4 portfolios. Portfolios 1 and 2 have the smallest size. Turning to portfolio returns in Panel B, portfolio returns increase with the portfolio duration from portfolio 1 to portfolio 4 and then decrease from portfolio 4 to portfolio 10. Portfolio 1 has a monthly average of 1.05%; portfolio 4 has the highest monthly average return of 2.28%, and portfolio 10 has the lowest monthly return of only 0.01%. Figure 1 further illustrates this pattern. Hence, we see that the equity yield curve is hump-shaped, although it has an overall downward slope. Gonçalves (2021a) finds a similar hump-shaped term structure of dividend claims, using a Nelson and Siegel (1987) term structure model to fit the yields from dividend strips.[17] Risk-adjusted portfolio returns from various asset pricing models (i.e., portfolio alphas) show similar patterns. For example, the CAPM alpha of portfolio 1 is 0.19%, whereas it is 1.20% and –0.77% in portfolios 4 and 10, respectively. The return difference between portfolio 10 and portfolio 1 is significantly negative (i.e., CAPM alpha = –0.96%; *t*-statistic = –1.68), and the return difference between portfolio 10 and portfolio 4 is even more negative (i.e., CAPM alpha = –1.98%; *t*-statistic = –2.02).

Next, I examine the long-term effects of the effective equity duration using a holding period from 3 to 36 months. For easy comparison, I scale the holding-period returns and alphas by the number of holding months. Figure 2 reports the average monthly portfolio returns for 4 representative cases with holding periods of 3, 6, 12, and 30 months. More results are reported in Appendix D of the Supplementary Material. First, we see a similar hump-shaped yield curve when the holding period is short (3 or 6 months), but it becomes less apparent when the holding period is longer. Second, the portfolio with the highest return shifts from portfolio 4 to portfolio 2 when the holding period increases. Third, using the Fama–French 5-factor model as the benchmark, Appendix D in the Supplementary Material shows that the return difference between long- and short-duration portfolios remains significantly negative up to 30 months, but it becomes insignificant with a 36-month holding period. That is, the duration effect lasts up to 30 months.

[16]See, for example, Binsbergen et al. (2012), (2013), Binsbergen and Koijen (2017), Giglio, Maggiori, and Stroebel (2015), Dew-Becker, Giglio, Le, and Rodriguez (2017), Lustig, Stathopoulos, and Verdelhan (2018), and Backus, Boyarchenko, and Chernov (2018). Some articles challenge the downward-sloping pattern, citing reasons like microstructure noise, taxation, and trading costs (Boguth, Carlson, Fisher, and Simutin (2012), Schulz (2016), and Bansal, Miller, Song, and Yaron (2019)). Also see Appendix C in the Supplementary Material for some theoretical discussions of the yield curve.

[17]Chen and Li (2019) and Gormsen and Lazarus (2019) also find some weak evidence of a hump-shaped term structure. Gonçalves (2021a) proposes that long-duration assets hedge against equity reinvestment risk and models this in the intertemporal CAPM to generate a hump-shaped term structure.

TABLE 2

The Equity Yield Curve Implied by the Effective Equity Duration

All stocks in Table 2 are sorted into 10 portfolios based on the effective equity duration of individual stocks estimated in the previous month. I compute the average firm size, the value-weighted portfolio duration, monthly returns, and the alphas from the capital asset pricing model (CAPM) (α_{CAPM}), the Fama–French 3-factor model (α_{FF3}), and the Fama–French 5-factor model (α_{FF5}). Panel A presents the average firm size (SIZE, in \$millions) and duration (*D*) of the 10 portfolios. Panel B presents the average monthly portfolio returns and alphas. Newey–West *t*-statistics with 6 lags are in parentheses. The heading "10−4" indicates the difference between portfolio 10 and portfolio 4, and "10−1" indicates the difference between portfolio 10 and portfolio 1. Returns and alphas are reported in percentages. The sample period is 1995–2016.

Portfolio	1	2	3	4	5	6	7	8	9	10	10−4	10−1
Panel A. Portfolio Characteristics												
SIZE (\$millions)	5,210.74	5,450.52	6,009.35	6,308.51	6,189.75	6,847.21	5,792.75	6,258.57	5,877.18	6,422.07	113.56	1,211.33
D	3.39	8.01	12.50	16.96	21.82	27.39	34.45	43.51	59.50	114.96	98.00	111.57
Panel B. Portfolio Returns												
Raw return	1.05	1.56	1.62	2.28	0.74	0.45	0.45	0.31	0.55	0.01	−2.27	−1.04
	(1.69)	(1.94)	(1.43)	(1.92)	(1.57)	(0.63)	(0.51)	(0.43)	(0.79)	(0.01)	(−2.10)	(−1.84)
α_{CAPM}	0.19	0.61	0.55	1.20	−0.26	−0.38	−0.48	−0.65	−0.29	−0.77	−1.98	−0.96
	(0.48)	(1.48)	(0.88)	(1.53)	(−0.55)	(−0.98)	(−1.00)	(−1.68)	(−0.89)	(−1.40)	(−2.02)	(−1.68)
α_{FF3}	0.21	0.86	0.84	1.51	−0.11	−0.31	−0.07	−0.27	−0.36	−0.72	−2.24	−0.93
	(0.54)	(2.04)	(1.12)	(1.75)	(−0.22)	(−0.80)	(−0.15)	(−0.76)	(−1.21)	(−1.47)	(−2.02)	(−1.65)
α_{FF5}	−0.02	1.02	0.42	1.37	−0.03	−0.45	−0.21	−0.25	−0.37	−0.72	−2.09	−0.70
	(−0.07)	(2.48)	(0.63)	(1.78)	(−0.08)	(−1.21)	(−0.46)	(−0.59)	(−1.04)	(−1.32)	(−2.12)	(−1.63)

FIGURE 1

The Equity Yield Curve Implied by the Effective Equity Duration

Figure 1 plots the value-weighted monthly returns and duration for 10 portfolios, which are sorted by the effective equity duration of individual stocks estimated in the previous month. The sample period is 1995–2016.

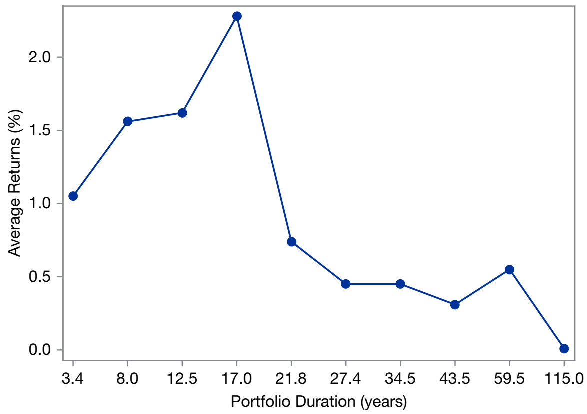
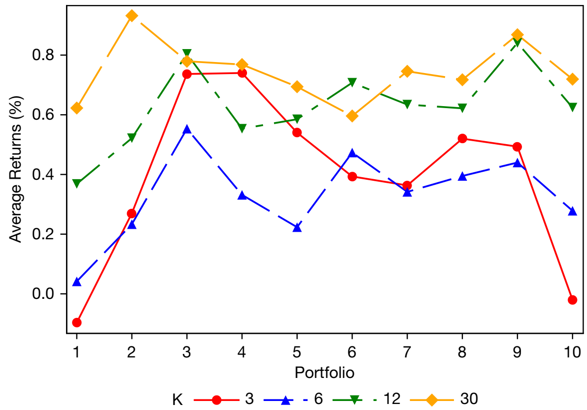


FIGURE 2

Average Monthly Returns of 10 Duration-Sorted Portfolios with Various Holding Periods

Figure 2 shows the value-weighted average returns of 10 portfolios sorted by the effective equity duration. The 10 portfolios are held for K (K = 3, 6, 12, 30) months. For easy comparison, the K-month holding returns are scaled by the number of holding months (K) and plotted in this figure. The sample period is 1995–2016.



Last, I perform extensive robustness checks. To save space, I report details in Appendix E of the Supplementary Material. I first consider various features of FOMC announcements that might affect market reactions. For example, I exclude FOMC announcements that are not prescheduled and those that coincide with other macroeconomic news announcements (including CPI, PPI, and employment news) or change the monetary policy path between expansion and contraction. I also differentiate FOMC announcements during expansion and recession periods. Next, I consider alternative event windows, such as using the same event window for

CME Federal Funds futures and stocks, $[s-30, s+10]$. Last, I consider alternative VAR specifications (e.g., including more state variables). In addition to the five state variables used in the main case, I include the risk-free rate, which has been shown to predict future market returns (Campbell et al. (2018)). I find that the results are robust under these variations.

C. The Equity Yield Curve Implied by the Dechow et al. Duration

In this subsection, I compare the equity yield curves implied by the effective equity duration and the Dechow et al. (2004) duration. Table 3 presents the average firm size, portfolio duration, monthly returns, and alphas from various asset pricing models for 10 portfolios sorted by the Dechow et al. duration. Panel A shows that the portfolio duration increases from 10.98 years in portfolio 1 to 22.16 years in portfolio 10, a spread of 11.18 years. The firm size increases over portfolios 1–8 and then decreases over portfolios 9 and 10. Turning to the returns, we see that the average monthly portfolio returns decrease from 1.02% in portfolio 1 to 0.07% in portfolio 10. The return difference between portfolios 10 and 1, –0.94% per month, is significantly negative. Its alphas are also significantly negative for the CAPM and the Fama–French 3-factor model but not for the Fama–French 5-factor model. Figure 3 plots the equity yield curve with the Dechow et al. duration measure. As in Weber (2018), Figure 3 shows an overall downward-sloping yield curve,[18] which is unlike the hump-shaped yield curve implied by the effective equity duration.

D. Understanding the Equity Yield Curve

Using the Macaulay duration (e.g., the Dechow et al. (2004) duration) typically generates a downward-sloping yield curve for the future cash flows of risky assets. That is, the expected returns decrease with the Macaulay duration. In other words, when the expected returns increase, far-distant future cash flows become less important, and the Macaulay duration is lower. However, the effective equity duration gives a hump-shaped yield curve, as shown in Figure 1. That is, the portfolio returns increase (decrease) with the effective equity duration when the duration is short (long). For example, we see that portfolio 4 has the highest average returns. How can these two seemingly different findings be reconciled? The answer rests on the comovement between the expected future cash-flow growth and expected returns.

Remember that equation (9) suggests that the effective equity duration differs from the Macaulay duration in that it captures the sensitivity of expected future cash-flow growth with respect to the expected returns (i.e., $(\Delta Eg_{i,t}/\Delta Er_{i,t})$). Menzly et al. (2004), Lettau and Ludvigson (2005), and Binsbergen and Koijen (2010) show that the expected cash-flow growth increases with the expected returns (i.e., $(\Delta Eg_{i,t}/\Delta Er_{i,t} > 0)$). Therefore, an increase in the expected returns has two opposite effects on stock duration. First, when the expected returns increase, the Macaulay duration decreases, which decreases the effective equity duration. Second, the future cash-flow growth increases with the expected returns, which makes

[18]There are some minor zigzag patterns, likely due to the short sample period.

TABLE 3

The Equity Yield Curve Implied by the Dechow et al. (2004) Duration

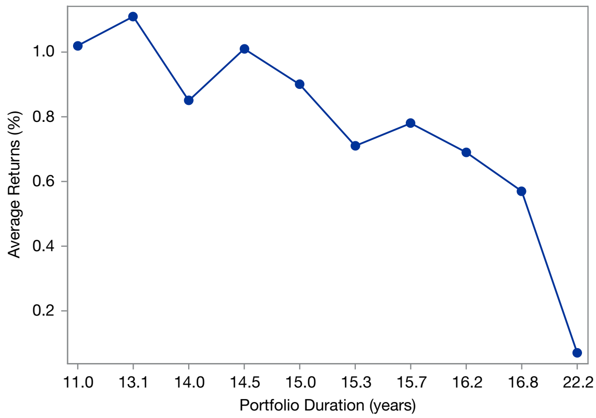
All stocks in Table 3 are sorted into 10 portfolios based on the duration of individual stocks estimated in the previous month. Duration is computed as in Dechow et al. (2004). I compute the average firm size (in $ millions), the value-weighted portfolio duration, monthly returns, and the alphas from the capital asset pricing model (CAPM) (α_{CAPM}), the Fama–French 3-factor model (α_{FF3}), and the Fama–French 5-factor model (α_{FF5}). Panel A presents the average firm size (SIZE) and duration (D^{DSS}) of the 10 portfolios. Panel B presents the average monthly portfolio returns and alphas. Newey–West *t*-statistics with 6 lags are in parentheses. The heading "10 − 1" indicates the difference between portfolio 10 and portfolio 1. Returns and alphas are reported in percentages. The sample period is 1995–2016.

Portfolio	1	2	3	4	5	6	7	8	9	10	10 − 1
Panel A. Portfolio Characteristics											
SIZE ($millions)	1,775.44	3,250.56	4,100.81	4,883.87	5,735.35	7,217.82	8,130.65	8,831.62	4,636.51	1,384.86	−390.58
D^{DSS}	10.98	13.14	13.98	14.52	14.97	15.33	15.73	16.16	16.83	22.16	11.18
Panel B. Portfolio Returns											
Raw return	1.02	1.11	0.85	1.01	0.90	0.71	0.78	0.69	0.57	0.07	−0.94
	(2.26)	(3.10)	(2.73)	(2.95)	(3.53)	(2.09)	(2.69)	(2.25)	(1.34)	(0.12)	(−1.78)
α_{CAPM}	0.19	0.36	0.15	0.3	0.26	0.01	0.08	0	−0.29	−1.09	−1.28
	(0.58)	(1.53)	(0.76)	(1.59)	(1.60)	(0.03)	(0.97)	(−0.01)	(−1.07)	(−3.14)	(−2.33)
α_{FF3}	−0.05	0.21	0.02	0.17	0.18	−0.06	0.11	0.1	−0.09	−0.94	−0.89
	(−0.23)	(1.26)	(0.11)	(1.12)	(1.30)	(−0.41)	(1.34)	(0.79)	(−0.61)	(−3.19)	(−2.51)
α_{FF5}	−0.16	0.05	−0.19	0.02	−0.03	−0.27	0.02	−0.02	0.13	−0.51	−0.35
	(−0.69)	(0.28)	(−1.32)	(0.12)	(−0.26)	(−1.79)	(0.22)	(−0.14)	(0.85)	(−1.82)	(−0.91)

FIGURE 3

The Equity Yield Curve Implied by the Dechow et al. Duration

Figure 3 plots the value-weighted monthly returns and duration for 10 portfolios, which are sorted by the duration of individual stocks estimated in the previous month. Stock duration is estimated as in Dechow et al. (2004). The sample period is 1995–2016.



cash flows in the far-distant future more important and hence increases the effective equity duration. Overall, the expected returns increase with the effective equity duration if the latter effect dominates the former, and vice versa. This suggests that portfolio 4 likely has a high correlation between the expected cash-flow growth and its expected return because Portfolio 4 has the highest average returns. I examine this conjecture in this subsection.

Like Binsbergen and Koijen (2010), I estimate a VAR model of annual dividend growth and annual returns with an extending window to predict future dividend growth rates and expected returns in each year. The first observation starts in 1985, and I require at least 8 annual observations to estimate the VAR system. Next, in each year, given the estimates in the last step, I compute the correlation between the expected future dividend growth and the expected returns for each stock. Last, I compute the simple average correlation for the 10 duration-sorted portfolios. Figure 4 plots the average correlation of these 10 portfolios. As expected, portfolio 4 has the highest correlation of 0.25, whereas portfolios 1 and 10 have correlations of 0.1 and 0.15, respectively.[19] In fact, the correlation plot shows a hump shape, which is similar to the yield curve.

E. Effective Equity Duration and Firm Characteristics

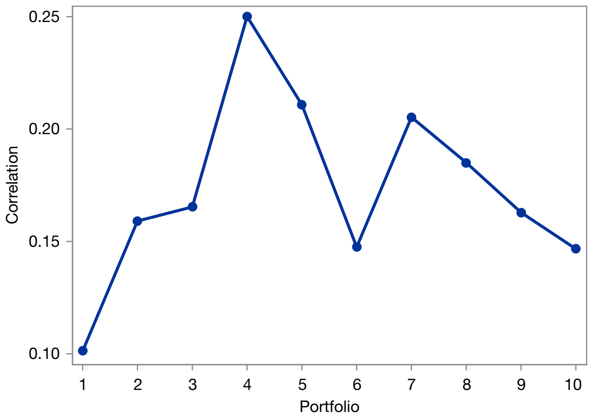
Firm characteristics often contain information about future dividend growth and expected returns. One might wonder how these characteristics relate to the effective equity duration. In this subsection, I run panel regressions of the duration against some firm characteristics to explore their connections, and the results are

[19]Binsbergen and Koijen (2010) find a correlation of 0.417 with a standard deviation of 0.375 for the market portfolio. My estimates are smaller because the correlation is estimated at the individual stock level.

FIGURE 4

Correlation between Expected Dividend Growth and Discount Rates

Figure 4 plots the average correlation between expected dividend growth and the discount rate for 10 portfolios sorted by the effective equity duration.



reported in Table 4. Following Gonçalves (2021b) and Gormsen and Lazarus (2019), I include previous market leverage (MARKET_LEVERAGE, measured as the book value of short-term and long-term debts divided by the market value of assets), asset growth (ASSET_GROWTH, measured as the annual growth rate of total assets), dividend growth rate (DIVIDEND_GROWTH, measured as the annual cash dividend growth rate), book-to-market equity (B/M), and gross profitability (PROFITABILITY). Firm and time fixed effects are included. Columns 1–3 use the effective equity duration, whereas column 4 reports the results using the Dechow et al. (2004) duration.

Column 1 reports the results using all stocks. Consistent with intuition, the effective equity duration increases with market leverage but decreases with the realized dividend growth rate. Also, as shown by Chen and Li (2019), Gonçalves (2021b), and Gormsen and Lazarus (2019), both B/M and gross profitability negatively correlate with the duration (i.e., value and profitable stocks generally have a shorter duration). However, a different picture is evident when the sample is separated into two subsamples of short-duration and long-duration stocks in columns 2 and 3, respectively. Stocks with a duration below (above) the 40th percentile of the cross section are short-duration (long-duration) stocks. Column 2 shows that gross profitability is positively correlated with duration. That is, among short-duration stocks, more profitable firms have a longer duration. Column 3 suggests that B/M is negatively correlated with duration. That is, among long-duration stocks, value firms have a shorter duration. This might explain why the value and profitability premia appear to hedge against each other (Novy-Marx (2013) and Wahal (2019)). Turning to the Dechow et al. (2004) duration in column 4, the Dechow et al. duration is negatively correlated with both B/M and gross profitability, which is similar to the findings documented by Chen and Li (2019) and Gonçalves (2021b). Such results highlight the difference between the effective equity duration and the Macaulay duration.

TABLE 4

Panel Regressions of Duration Against Firm Characteristics

Table 4 reports the panel-regression results of duration against firm characteristics, including market leverage (MARKET_LEVERAGE, measured as the book value of short-term and long-term debts divided by the market value of assets), asset growth (ASSET_GROWTH, measured as the annual growth rate of total assets), dividend growth rate (DIVIDEND_GROWTH, measured as the annual cash dividend growth rate), book-to-market equity (B/M), and gross profitability (PROFITABILITY). Columns 1–3 use the effective equity duration. Column 1 uses all stocks. Columns 2 and 3 use subsamples of short-duration and long-duration stocks, respectively. Stocks with a duration below (above) the 40th percentile of the cross section are short-duration (long-duration) stocks. Column 4 reports the results using the Dechow et al. (2004) duration. Firm and time fixed effects are included. *t*-statistics are in parentheses. The sample period is 1995–2016.

	Effective Equity Duration			DSS Duration
	All Stocks	Short-Duration Stocks	Long-Duration Stocks	All Stocks
	1	2	3	4
MARKET_LEVERAGE	29.44	4.79	22.58	−0.90
	(7.02)	(5.21)	(4.86)	(−9.77)
ASSET_GROWTH	−2.10	−0.83	3.47	0.32
	(−1.56)	(−3.11)	(1.95)	(8.01)
DIVIDEND_GROWTH	−5.72	0.25	−8.71	−0.41
	(−3.95)	(0.84)	(−5.02)	(−10.31)
B/M	−12.23	−0.17	−5.18	−1.08
	(−8.28)	(−0.39)	(−3.97)	(−24.92)
PROFITABILITY	−12.81	2.58	5.49	−2.61
	(−2.42)	(2.24)	(0.92)	(−16.13)
Fixed effects	Yes	Yes	Yes	Yes
R^2	0.76	0.93	0.91	0.87

F. Effective Equity Duration and Monetary Policy Risk

Ozdagli and Velikov (2020) study how monetary policy risk affects the cross section of stock returns. They use some observable firm characteristics to construct a proxy of MPE for stocks and show that stocks that react more positively to expansionary monetary policy (high-MPE stocks) have lower future returns because these stocks hedge against the monetary policy risk. Although both the effective equity duration and MPE use stock price reactions around FOMC surprises, they are different. First, MPE essentially captures stock return sensitivities to changes in the interest rate (i.e., $-(\Delta P_{i,t}/P_{i,t,s-})/\Delta R_{f,t}$), which is the dollar duration ((Jiang and Sun (2019)). However, the effective equity duration captures the stock return sensitivities to the changes in expected returns, as shown in equation (14). $\Delta R_{f,t}$ is only part of the denominator of equation (14). Second, MPE and the effective equity duration rely on different sources to generate cross-sectional variations. Because $\Delta R_{f,t}$ is common across all stocks, the event returns $(\Delta P_{i,t}/P_{i,t,s-})$ drive the cross-sectional variations of MPE.[20] Compared with the changes in expected market returns ($\Delta \mathrm{ER}_{M,t}$), $\Delta R_{f,t}$ is often very tiny. Therefore, equation (14) suggests that the difference in betas, in addition to the difference in event returns, drives the cross-sectional duration variations.

I closely follow Ozdagli and Velikov (2020) to construct MPE. MPE barely correlates with the effective equity duration (with a correlation coefficient of –0.03). Next, I independently sort stocks based on their duration and MPE into quintile portfolios. Table 5 presents the value-weighted monthly returns and alphas of

[20]Ozdagli and Velikov (2020) use firm characteristics to provide some additional cross-sectional variations to MPE.

TABLE 5

Duration–MPE Sorted Portfolio Returns

Table 5 shows the value-weighted monthly returns and alphas of quintile portfolios independently sorted by the effective equity duration and monetary policy exposure (MPE). MPE is estimated as in Ozdagli and Velikov (2020). Alphas are computed from the capital asset pricing model (CAPM) (α_{CAPM}), the Fama–French 3-factor model (α_{FF3}), and the Fama–French 5-factor model (α_{FF5}). "LONG − SHORT" refers to the return difference between the long- and short-duration portfolios. "HIGH − LOW" refers to the return difference between the high- and low-MPE portfolios. Newey–West *t*-statistics with 6 lags are in parentheses. Returns and alphas are reported in percentages. The sample period is 1995–2016.

	Duration Quintiles					
MPE	Short	2	3	4	Long	LONG − SHORT
Panel A. Raw Returns						
Low	1.89	1.88	1.26	1.68	1.93	0.04
	(2.18)	(1.72)	(1.73)	(1.86)	(2.29)	(0.06)
2	1.24	1.27	0.10	1.52	1.12	−0.12
	(1.94)	(2.22)	(0.11)	(2.28)	(1.42)	(−0.21)
3	1.7	0.95	0.32	0.89	1.11	−0.59
	(2.02)	(1.13)	(0.41)	(0.95)	(1.11)	(−0.69)
4	1.58	1.00	1.32	0.84	0.1	−1.47
	(1.56)	(1.33)	(1.45)	(1.35)	(0.2)	(−1.91)
High	2.36	1.55	0.68	−0.13	0.46	−1.9
	(2.12)	(1.40)	(1.05)	(−0.19)	(0.59)	(−2.01)
HIGH − LOW	0.47	−0.33	−0.58	−1.81	−1.47	
	(0.49)	(−0.29)	(−0.71)	(−1.80)	(−1.27)	
Panel B. α_{CAPM}						
Low	0.96	0.91	0.23	0.63	1.20	0.24
	(1.45)	(0.84)	(0.31)	(0.75)	(1.42)	(0.5)
2	0.38	0.35	−0.71	0.62	0.44	0.06
	(0.79)	(0.59)	(−0.80)	(1.01)	(0.69)	(0.1)
3	0.75	0.04	−0.56	0.11	0.33	−0.41
	(1.53)	(0.06)	(−0.72)	(0.11)	(0.46)	(−0.49)
4	0.55	0.07	0.27	0.04	−0.76	−1.31
	(1.11)	(0.16)	(0.6)	(0.09)	(−2.26)	(−2.08)
High	1.41	0.32	−0.09	−1.03	−0.34	−1.75
	(1.77)	(0.61)	(−0.23)	(−1.99)	(−0.76)	(−1.90)
HIGH − LOW	0.45	−0.59	−0.32	−1.66	−1.54	
	(0.45)	(−0.53)	(−0.40)	(−1.68)	(−1.38)	
Panel C. α_{FF3}						
Low	0.88	0.64	−0.8	0.99	0.1	−0.78
	(1.39)	(0.73)	(−1.31)	(1.28)	(0.16)	(−2.01)
2	−0.12	−0.13	−1.05	0.25	−0.07	0.05
	(−0.29)	(−0.25)	(−0.98)	(0.46)	(−0.16)	(0.1)
3	0.57	−0.6	−0.82	−0.06	−0.23	−0.8
	(0.95)	(−0.99)	(−1.05)	(−0.08)	(−0.24)	(−0.70)
4	0.62	−0.14	0.18	−0.34	−1.19	−1.81
	(0.91)	(−0.31)	(0.34)	(−0.96)	(−3.31)	(−2.35)
High	1.55	1.22	−0.02	−0.59	−0.11	−1.66
	(2.43)	(1.57)	(−0.05)	(−1.39)	(−0.26)	(−1.90)
HIGH − LOW	0.67	0.58	0.78	−1.58	−0.21	
	(0.7)	(0.61)	(0.8)	(−2.08)	(−0.24)	
Panel D. α_{FF5}						
Low	0.85	0.29	−0.64	1.17	0.26	−0.59
	(1.08)	(0.37)	(−1.05)	(1.73)	(0.35)	(−1.32)
2	−0.29	−0.33	−0.73	0.07	−0.19	0.1
	(−0.74)	(−0.51)	(−0.82)	(0.13)	(−0.38)	(0.18)
3	0.39	−0.56	−0.58	−0.44	−0.78	−1.16
	(−0.62)	(−0.94)	(−0.76)	(−0.68)	(−1.03)	(−1.21)
4	0.63	−0.36	0.04	−0.5	−1.19	−1.82
	(1.12)	(−0.98)	(0.08)	(−1.39)	(−3.40)	(−2.71)
High	1.27	0.88	−0.19	−0.61	−0.08	−1.35
	(1.99)	(1.33)	(−0.43)	(−1.26)	(−0.17)	(−1.63)
HIGH − LOW	0.42	0.59	0.45	−1.79	−0.34	
	(0.39)	(0.59)	(0.51)	(−2.39)	(−0.34)	

quintile portfolios. The table shows that the duration effect exists among the two groups with the highest MPE. For example, for the highest-MPE group, the LONG − SHORT strategy has a negative return of –1.90% per month (t-statistic = –2.01), and its α_{CAPM} = –1.75% (t-statistic = –1.90). Similarly, the MPE effect exists among the DURATION = 4 group. The HIGH − LOW strategy has a negative return of –1.81% per month (t-statistic = –1.80), and its $\alpha_{\text{FF3}} = -1.58\%$ (t-statistic = –2.08). Overall, the double-sorting results show that the duration effect and MPE effect still exist after controlling for each other. This suggests that the effective equity duration captures some information other than MPE.

V. Investigating Measurement Errors[21]

Several sources might introduce measurement errors when applying equation (14) to estimate the effective equity duration. For example, the use of TAQ data to measure the high-frequency stock price reactions to monetary policy shocks might suffer from microstructure noise. In addition, the use of a daily VAR system to estimate the changes in the expected market returns might be less accurate. I investigate these potential measurement errors in this section.

A. Placebo Tests

The use of high-frequency data to measure stock price reactions over a short event window may be influenced by microstructure noise. To minimize microstructure noise, I exclude small stocks (e.g., stocks with a market capitalization below the NYSE size breakpoint of the 20th percentile). In this subsection, I further perform some placebo tests to examine whether the stock price reactions indeed pick up FOMC surprises around FOMC announcements. For each FOMC surprise, I use the data on the same weekday 4 weeks before and 4 weeks after FOMC announcements to do the placebo tests.[22] Taking the FOMC surprise on May 6, 2003, as an example, I choose Apr. 8, 2003, and June 3, 2003, as the placebo dates and use the same time window as the FOMC event window. I follow the same procedures as previously described to measure stock price reactions from TAQ data and to estimate market βs and the changes in expected market returns on the placebo test dates. I then apply equation (14) to estimate the effective equity duration on the placebo test dates. Because there are no FOMC surprises on these placebo test dates, I set $\Delta R_{f,t}$ as 0 when applying equation (14).

Figure 5 compares the probability density of event returns on FOMC announcement dates and placebo test dates. I divide the sample into negative and positive FOMC surprise subsamples because they have different effects on the distribution of event returns. First, Figure 5 shows that the event returns are symmetrically distributed around 0 on the placebo test dates, regardless of whether they are 4 weeks before or after negative/positive FOMC announcements. That is, the average event return is 0, which suggests that no systemic information affects the stock prices on the placebo test dates. Those realized returns are driven mainly by microstructure noise. Second, FOMC surprises clearly have information

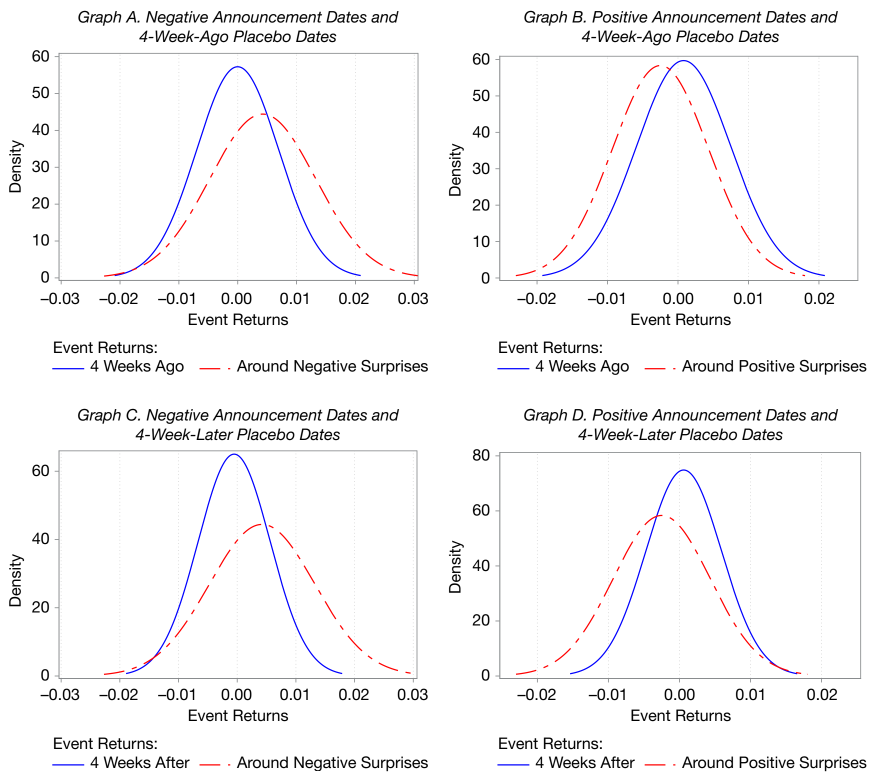
[21]I thank Andrei Gonçalves for suggesting some tests.

[22]I choose the same weekday to avoid potential weekday effects.

FIGURE 5

Probability Density of Event Returns on FOMC Announcement Dates and Placebo Dates

Figure 5 plots the probability density of event returns on Federal Open Market Committee (FOMC) announcement dates and placebo test dates. Graphs A and B use the same weekday 4 weeks before FOMC announcements as the placebo test dates. Graphs C and D use the same weekday 4 weeks after FOMC announcements as the placebo test dates. Graphs A and C plot a subsample of the negative FOMC surprises. Graphs B and D plot a subsample of the positive FOMC surprises. The sample period is 1995–2016.



content. For example, event returns are on average positive (negative) after negative (positive) FOMC surprises. Last, I use their empirical distribution functions to test whether event returns on placebo test dates and FOMC announcement dates have identical distributions. For both the positive and negative FOMC surprise subsamples, the Kolmogorov–Smirnov test strongly rejects the null hypothesis that event returns on the FOMC announcement dates and the placebo test dates are from the same distribution (asymptotic p-value < 0.0001).

Table 6 presents the average monthly returns and alphas of 10 portfolios sorted by the effective equity duration, which is estimated on placebo test dates. We see that these 10 portfolios have indistinguishable returns. For example, the alphas from the CAPM (α_{CAPM}), the Fama–French 3-factor model (α_{FF3}), and the Fama–French 5-factor model (α_{FF5}) are mostly indistinguishable from 0. The return difference between portfolios 10 and 1 or 4 is indistinguishable from 0. Again, Table 6 suggests that placebo test dates do not contain information observed on the FOMC surprise dates. Overall, the placebo tests show that FOMC surprises cause nontrivial

TABLE 6
Portfolio Returns on Placebo Test Dates

Table 6 presents the average monthly returns and alphas of 10 portfolios sorted by the effective equity duration. The effective equity duration is estimated on placebo test dates. Panel A uses the same weekday 4 weeks before Federal Open Market Committee (FOMC) surprises as the placebo test dates. Panel B uses the same weekday 4 weeks after FOMC surprises as the placebo test dates. Alphas are computed from the capital asset pricing model (CAPM) (α_{CAPM}), the Fama–French 3-factor model (α_{FF3}), and the Fama–French 5-factor model (α_{FF5}). Newey–West *t*-statistics with 6 lags are in parentheses. The heading "10 − 4" indicates the difference between portfolio 10 and portfolio 4, and "10−1" indicates the difference between portfolio 10 and portfolio 1. Returns and alphas are reported in percentages. The sample period is 1995–2016.

Portfolio	1	2	3	4	5	6	7	8	9	10	10 − 4	10 − 1
Panel A. 4 Weeks Before FOMC Announcements												
Raw return	1.24	1.11	0.61	0.75	0.05	0.42	0.61	0.74	0.48	1.04	0.29	−0.2
	(2.00)	(2.28)	(0.84)	(1.11)	(0.09)	(0.94)	(0.98)	(1.06)	(0.71)	(1.19)	(0.52)	(−0.20)
α_{CAPM}	0.21	0.06	−0.50	−0.32	−0.85	−0.40	−0.36	−0.08	−0.31	0.06	0.38	−0.15
	(0.49)	(0.27)	(−1.36)	(−0.62)	(−2.14)	(−1.22)	(−0.63)	(−0.22)	(−0.45)	(0.07)	(0.73)	(−0.15)
α_{FF3}	0.53	−0.21	−0.15	0.25	−0.85	−0.19	0.28	0.44	−0.17	0.52	0.28	−0.01
	(1.13)	(−0.71)	(−0.42)	(0.63)	(−2.26)	(−0.39)	(0.44)	(1.05)	(−0.24)	(0.54)	(0.35)	(−0.01)
α_{FF5}	0.59	−0.28	−0.38	−0.1	−1.22	−0.58	0.17	0.24	−0.64	0.56	0.66	−0.03
	(1.09)	(−0.78)	(−0.80)	(−0.24)	(−3.48)	(−1.12)	(0.23)	(0.61)	(−0.84)	(0.56)	(0.80)	(−0.03)
Panel B. 4 Weeks After FOMC Announcements												
Raw return	−0.08	0.41	−0.15	0.87	−0.03	0.29	0.64	0.40	−0.03	0.46	−0.41	0.54
	(−0.09)	(0.68)	(−0.13)	(1.33)	(−0.04)	(0.52)	(1.21)	(0.50)	(−0.03)	(0.63)	(−0.88)	(1.11)
α_{CAPM}	−0.53	−0.03	−0.62	0.45	−0.46	−0.13	0.26	0.00	−0.41	0.11	−0.34	0.64
	(−1.07)	(−0.07)	(−0.75)	(1.14)	(−1.39)	(−0.59)	(0.59)	(−0.01)	(−0.90)	(0.26)	(−0.59)	(1.28)
α_{FF3}	−0.53	−0.26	−0.17	0.56	−0.26	−0.05	0.05	0.00	−0.54	−0.14	−0.70	0.39
	(−1.08)	(−0.61)	(−0.25)	(1.09)	(−0.78)	(−0.17)	(0.08)	0.00	(−0.93)	(−0.24)	(−0.93)	(0.63)
α_{FF5}	−0.49	−0.10	−0.09	0.68	−0.29	−0.11	0.25	0.11	−0.56	−0.17	−0.85	0.32
	(−1.12)	(−0.21)	(−0.16)	(1.34)	(−0.93)	(−0.32)	(0.36)	(0.40)	(−1.10)	(−0.29)	(−1.01)	(0.52)

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stock price reactions that are not driven by microstructure noise. It is important to use FOMC surprises as the informational events.

B. Using Alternative Estimates of Changes in the Expected Market Returns

This article uses a VAR system to infer the changes in expected market returns. One might wonder whether the use of daily VAR incurs some estimation errors, for two reasons. First, the VAR approach may be sensitive to the specification. Second, the VAR approach is more often used with low-frequency data (e.g., monthly, quarterly, or annual data) in the macroeconomics literature.[23] I address these issues in 3 steps. First, I show that the results are robust under alternative VAR specifications in Appendix E of the Supplementary Material. Second, because financial markets provide high-frequency data, some articles use high-frequency VAR models to predict asset returns. For example, Campbell, Chacko, Rodriguez, and Viceira (2004) consider strategic asset allocation in a continuous-time VAR framework. Chordia, Sarkar, and Subrahmanyam (2004) use a daily VAR model to predict returns and liquidity in stock and Treasury bond markets. Using daily data, DeMiguel, Nogales, and Uppal (2014) show that VAR models can capture stock return time-series dependence and improve the out-of-sample portfolio performance. Last, instead of using VAR estimates, I infer the changes in the expected market returns based on the estimates provided by Chabi-Yo and Loudis (2020) and compute the effective equity duration as another robustness check.

Based on the no-arbitrage condition, Chabi-Yo and Loudis (2020) derive the lower and upper bounds of expected excess market returns as functions of higher-order risk-neutral moments, which are estimated from S&P 500 index option prices. I use their unrestricted version of the lower and upper bounds of expected excess market returns, based on options with a maturity of 60 days.[24] I compute the average of the lower and upper bounds as the expected excess market returns and convert it into annualized rates. Together with the risk-free rate, this gives us daily expected market returns. Then the changes in expected market returns are defined as the first-order difference of expected market returns. The sample period is Jan. 1996 to Aug. 2015.

I first compare the distributions of changes in expected market returns, computed from the VAR system (denoted as VAR) or by Chabi-Yo and Loudis (2020) (denoted as CL). Figure 6 plots the probability density of these two sets of estimates. The VAR and CL estimates have similar means, but the CL estimates have a slightly smaller variance. I use their empirical distribution functions to test whether these two sets of estimates have identical distributions. The asymptotic p-value for the Kolmogorov–Smirnov test is 0.299; that is, I cannot reject the null hypothesis that they follow the same distribution.

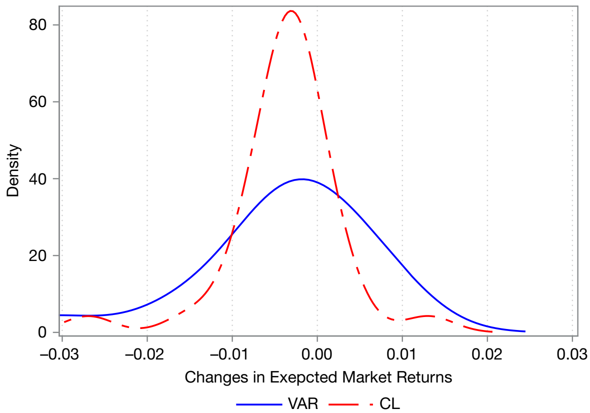
Next, I compute the effective equity duration using the changes in the expected market returns based on CL. Table 7 presents the average duration, monthly returns,

[23]This is largely because the macroeconomic data are monthly, quarterly, or even annual only.
[24]Data are available at https://sites.google.com/view/johnathan-a-loudis/research.

FIGURE 6

Probability Density of Changes in Expected Market Returns

Figure 6 plots the probability density of changes in the expected market returns. The changes in the expected market returns are estimated from a vector autoregressive (VAR) system (denoted as VAR) or computed from the lower and upper bounds of expected excess market returns, which are provided by Chabi-Yo and Loudis (2020). Specifically, the expected market returns are computed as the average of the lower and upper bounds of expected excess market returns, adjusted by the risk-free rate. The changes in expected market returns are defined as the first-order difference of the expected market returns (denoted as CL). The sample period is Jan. 1996–Aug. 2015.



and alphas of 10 portfolios sorted by the effective equity duration. First, these 10 portfolios have a duration similar to that reported in Table 2. Second, portfolio 4 has the highest average return of 2.26% per month, whereas portfolio 10 has the lowest average return of –0.97% per month. The return difference between portfolios 10 and 4 is significantly negative (i.e., $\alpha_{\text{FF5}} = -2.74\%$ and t-statistic = –2.14). Again, there is a hump-shaped yield curve, which is similar to that reported in Table 2. Overall, the results based on the CL estimates are qualitatively similar to those based on the VAR estimates. This validates the VAR approach.

C. Further Verification of the Effective Equity Duration

Equation (10) says that the effective equity duration captures the sensitivity of stock returns to changes in the discount rate. Therefore, I should observe stronger sensitivities for stocks with a longer duration. In this subsection, I use this conjecture to further verify the estimates of effective equity duration. Because it is difficult to precisely measure changes in the expected return for individual stocks, I rely on the changes in expected market returns, which are derived from Chabi-Yo and Loudis (2020). I apply the CAPM to compute changes in expected returns for individual stocks on each day. Next, for each stock, I regress stock returns against changes in the expected returns to estimate the sensitivity of stock returns to changes in the discount rate. Last, I compute the value-weighted sensitivities for 10 duration-sorted portfolios. All estimation is based on daily data from the past year. Figure 7 plots the sensitivity of stock returns to changes in the discount rate for the 10 portfolios. The figure shows that the long-duration portfolios have stronger sensitivities. For example, portfolio 1 has a sensitivity

TABLE 7

Portfolio Returns: Using Alternative Estimates of Changes in the Expected Market Returns

Table 7 presents the average duration, monthly returns, and alphas of 10 portfolios sorted by the effective equity duration. I use the lower and upper bounds of expected excess market returns from Chabi-Yo and Loudis (2020) to compute the changes in expected market returns and the effective equity duration. Specifically, the expected market returns are computed as the average of the lower and upper bounds of the expected market returns, adjusted by the risk-free rate. The changes in expected market returns are defined as the first-order difference of expected market returns. Alphas are computed from the capital asset pricing model (CAPM) (α_{CAPM}), the Fama–French 3-factor model (α_{FF3}), and the Fama–French 5-factor model (α_{FF5}). Newey–West t-statistics with 6 lags are in parentheses. The heading "10 − 4" indicates the difference between portfolio 10 and portfolio 4, and "10−1" indicates the difference between portfolio 10 and portfolio 1. Returns and alphas are reported in percentages. The sample period is Jan. 1996–Aug. 2015.

Portfolio	1	2	3	4	5	6	7	8	9	10	10-4	10-1
Panel A. Portfolio Duration												
D	3.08	6.87	10.70	14.65	19.48	25.17	32.63	42.58	60.08	123.51	108.86	120.43
Panel B. Portfolio Returns												
Raw return	1.26	0.76	1.16	2.26	0.40	−0.52	−0.27	−0.09	−0.04	−0.97	−3.23	−2.24
	(1.65)	(1.15)	(1.26)	(1.44)	(0.43)	(−0.77)	(−0.36)	(−0.08)	(−0.06)	(−1.31)	(−2.18)	(−2.51)
α_{CAPM}	0.89	0.43	0.78	1.87	−0.01	−0.89	−0.63	−0.45	−0.39	−1.31	−3.18	−2.19
	(2.03)	(0.85)	(1.71)	(1.66)	(−0.03)	(−2.01)	(−1.49)	(−0.74)	(−0.59)	(−2.30)	(−2.26)	(−2.45)
α_{FF3}	0.53	0.38	1.09	2.15	0.79	−1.20	−0.36	0.54	−0.36	−1.12	−3.27	−1.65
	(1.05)	(0.78)	(2.21)	(1.51)	(1.15)	(−2.57)	(−0.66)	(0.51)	(−0.51)	(−1.41)	(−1.82)	(−1.56)
α_{FF5}	0.33	0.42	1.03	1.99	0.82	−1.04	−0.22	0.43	0.05	−0.75	−2.74	−1.08
	(0.76)	(0.95)	(2.04)	(1.58)	(1.17)	(−2.86)	(−0.39)	(0.46)	(0.14)	(−1.85)	(−2.14)	(−2.41)

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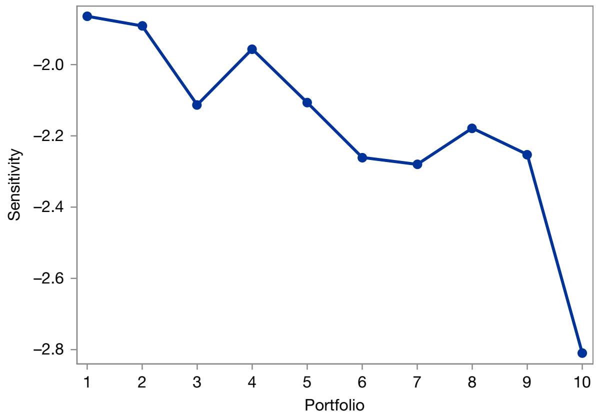
FIGURE 7

Stock Return Sensitivity to Changes in Discount Rates

Figure 7 plots the sensitivity of stock returns to changes in the discount rate for 10 portfolios sorted by the effective equity duration. Changes in the expected returns for individual stocks are computed from the capital asset pricing model (CAPM) using the changes in the expected market returns computed from Chabi-Yo and Loudis (2020). The sensitivity of stock returns to changes in the discount rate is computed from regressing stock returns against changes in the expected returns. Portfolio sensitivity is computed as the valued-weighted sensitivities of individual stocks. The sample period is Jan. 1996–Aug. 2015.



of –1.86, whereas portfolio 10 has a sensitivity of –2.81. This qualitatively supports the conjecture.[25]

VI. Conclusions

Discount rates affect stock prices. The traditional Macaulay duration captures only the direct effect of discount rates on asset prices via the discount-rate channel, assuming that the expected future cash-flow growth does not change with the discount rate. However, for stocks, the expected future cash-flow growth usually increases with the expected returns. Therefore, discount rates can indirectly influence stock prices via the cash-flow channel. This article proposes a new duration measure, the effective equity duration, to capture the total effects of discount rates on asset prices. This is useful for portfolio-optimization and risk-management purposes. I use FOMC surprises as informational events to measure the effective equity duration. The effective equity duration presents a hump-shaped equity yield curve, which differs from the downward-sloping yield curve found with the Macaulay duration. That is, stock returns increase with the duration when the duration is relatively short, but the equity yield becomes downward-sloping when the duration is longer because the expected future cash-flow growth increases with the discount rate. Using the effective duration estimates, I find that gross profitability increases

[25]The magnitudes of sensitivities do not align well with those of duration estimates as a result of data limitations and estimation errors. First, sensitivities are estimated with daily data over the past year, whereas duration is mainly based on price information within a short event window. Second, I apply the CAPM on FOMC announcement dates to estimate the effective equity duration while using the CAPM over the past year to estimate the sensitivities. However, the CAPM might not perform well on nonannouncement dates, so this introduces measurement errors.

with duration among short-duration stocks, whereas book-to-market equity decreases with duration among long-duration stocks. This might help explain why the value and profitability premia hedge against each other (Novy-Marx (2013), Wahal (2019)). I further show that this new duration measure captures information other than monetary policy shocks. Last, I address the concerns of measurement errors by using placebo tests and alternative estimates of changes in expected market returns and find robust results.

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S0022109020000940.

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