Macroeconomic Announcements and the News that Matters Most to Investors☆

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Abstract

We study a large set of macroeconomic announcements (MAs), disentangle their news content, and estimate risk premia for each type of news in the cross-section of stocks. Our most interesting finding is that a portfolio that pays off around MAs that negatively impact the stock market commands a large and positive risk premium. Adding this portfolio to a position in the stock market substantially increases the Sharpe ratio, while reducing price impact exposure to MAs. We argue that this portfolio is risky, consistent with models of reinvestment risk. Our findings challenge equilibrium models predicting a negative relation between shocks to discount rates and marginal utility as well as stories of cash flow news arriving on MA days.

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1. Introduction

Recent studies find that average stock market returns are high on the day of (or slightly before) major Macroeconomic Announcement (MA) types, such as FOMC, inflation, and unemployment.[1] This finding ignores two features of MAs that are key for asset pricing. First, there are more than a few MA types that are closely followed by practitioners and that have historically generated a large impact on financial markets (see, e.g., Gilbert, Scotti, Strasser, and Vega (2017) for price impacts in Treasury bond markets). Second, this finding contains little information about the type of MA news that matters most to investors, which is key information if we want to understand how exposure to MA surprises is priced. MA surprises bundle primitive information relevant for valuing many assets and prominent models imply that exposure to such surprises must command a premium.[2] Unfortunately, inference is complicated by the fact that the nature of the information bundle varies strongly across MA types.

Our paper builds on the idea that the price impact of MA surprises in short-term and long-term government bonds, risky corporate bonds, and stocks (or, more generally, "news components") ultimately reveals the primitive information that moved expectations. We use these price impacts to disentangle the news content of a large set of MA types and estimate a risk premium for each primitive news component. Our approach is uniquely suited to answer additional questions important for asset pricing. For instance, if MAs impact stock prices, is it cash flow or discount rate news that matters most? If discount rates, is the price of discount rate risk positive or negative? As noted by Kozak and Santosh (2020), prominent asset pricing models disagree on whether high discount rates are considered a good or a bad state by investors.[3]

To answer these questions, we proceed in three stages. First, we qualify and quantify the news contained in each MA surprise n on day t, by estimating the short-term price impact

[1] See, e.g., Savor and Wilson (2013); Lucca and Moench (2015); Ai and Bansal (2018).

[2] Consider, for instance, the vast Intertemporal CAPM (ICAPM) literature with models inspired by the seminal work of Merton (1973).

[3] Similarly, Ozdagli and Velikov (2020) argue that models have opposing predictions for the price of exposure to FOMC monetary policy shocks.

(from the end of day $t-1$ to $t+2$), denoted $b_{k,n}$, on the four news components k (the 1 year yield, 10-1 year term spread, the BAA-10 year credit spread, and CRSP excess stock market returns). Our method is general and can easily accommodate other news components, such as expectations of growth, inflation or volatility. That said, the prices of the financial assets we study should already reflect these expectations to a large extent. Specifically, we study the top 25 MA types ranked by Bloomberg investor attention. We confirm empirically that studying few MA types ignores important news, because the most studied MA types are not always the ones that generate the largest price impact.[4]

In the second stage, we estimate exposures $\beta_{i,n}$ of individual stocks i to MA surprises S_n using two alternative methods that are standard in the literature. In the first method, exposures are a function of firm characteristics that previous literature has linked to monetary policy sensitivity and MA surprise sensitivity, more generally. As in Ozdagli and Velikov (2020), we estimate these exposures in-sample using a pooled regression of firm returns (in a short window around MAs) on MA surprises interacted with the firm characteristics. In the second method, we estimate "out-of-sample" exposures using an expanding window regression of firm returns on the MA surprises.

In the third stage, we estimate the unconditional risk premium for each news component k by sorting stocks on an aggregated exposure: $\beta_{i,k} = \sum_{n=1}^{N} \beta_{i,n} b_{k,n}$. Thus, the $b_{k,n}$ that disentangle news content in price impact regressions are used to weight stock's exposures $\beta_{i,n}$ to each MA type n. This approach allows us to estimate a risk premium for each separate news component, rather than a risk premium for each individual MA surprise that contains an unknown mix of information about the various news components. Because MA surprises explain only a small fraction of the variation in the news components at the three-day window, our approach is different from simply sorting stocks on their exposure to the news components in the short-window around MAs. Intuitively, such exposures are mostly based

[4]Another advantage is that many of the announcements we study do not suffer from issues that complicate inference for the FOMC announcement, which is the most popular MA type in the literature. The FOMC announcement is an active decision made (and potentially communicated before the announcement, see Vissing-Jorgensen (2020)) by the FOMC in response to the current state of the economy and financial markets. In contrast, the NFP announcement, for instance, simply sums the total number of workers in the United States.

on co-variation that is orthogonal to the MA surprise and thus would not tell us much about the price of MA risk.[5] Moreover, aggregation reduces noise (in the $\beta_{i,n}$s), which provides us with portfolios that hedge better ex post and a more powerful test of the null that MA risk is not priced. We test this null using the monthly CAPM α of the long-short quintile portfolio sorted on each $\beta_{i,k}$ over our sample from 1977 to 2019. Looking at CAPM α ensures that our results are not driven by exposure to the market portfolio (the usual proxy for the return on aggregate wealth in an ICAPM).

Let us first discuss the single most interesting and robust result that comes out of our third stage. When we use price impacts on the aggregate stock market portfolio to aggregate exposures (denoted $\beta_{i,MKT}$), we find that the resulting long-short portfolio captures a large and significant negative risk premium. The CAPM α ranges from -4.9% ($t = -2.5$) in the out-of-sample test to -8.0% ($t = -4.9$) in the in-sample test. This negative risk premium indicates that stocks that comove with MA surprises that have a positive (negative) price impact in the aggregate stock market have lower (higher) expected returns.[6][7] Our out-of-sample test is additionally interesting, because it shows that the long-short portfolio hedges MA surprises ex post. To be precise, when a 1$ investment in the aggregate stock market is combined with a short position of 1$ in the hedge portfolio, a significant 40% of the surprise impact in the stock market is eliminated. Combining, our results indicate that investors can partially eliminate the price impact of MAs, while increasing their average return. Indeed,

[5]This problem is not easily solved by looking at tighter windows. First, even in a 30-minute window, R^2s in the price impact regressions can be rather small (for instance, these R^2s equal 36% for the aggregate stock market and 8% for the long-term bond in Gürkaynak, Sack, and Swanson (2005a). Second, a large share of this tight-window price impact in the stock market may be due to price pressure (Boguth, Grégoire, and Martineau (2019)). Third, it is unlikely that individual stocks will fully incorporate the MA news in such a short window. That said, we show that our results are robust to using a shorter window of one day to estimate the price impacts $b_{k,n}$.

[6]A good example is the ADP employment surprise (measuring the monthly change in non-farm private employment), which has the largest positive impact on the stock market among all 25 MAs and the long-short portfolio sorted on exposure to this announcement captures a risk premium of -7.2% ($t = -3.93$).

[7]Savor and Wilson (2014) argue that the CAPM holds on announcement days, when the premium for market beta is relatively large, but not on other days. The main difference with their paper is that we estimate the premium for a portfolio that hedges only a specific component of the market return, that is, the return due to MAs. Furthermore, we differ by studying a much larger set of MA types (see also Ernst, Gilbert, and Hrdlicka, 2019) and estimating the premium as the unconditional average monthly return of the hedge portfolio.

we find that the Sharpe ratio of the hedged position is about 50% larger than the Sharpe ratio from investing in the market alone (0.76 versus 0.51 in the out-of-sample test).

What do these results say about asset pricing models? Why would investors consider stocks that comove with MA surprises that positively (negatively) impact the stock market so attractive as a hedge (risky)? We argue that this result can only be explained by a particular type of discount rate news, and not by cash flow news. If an MAs positive price impact is due to news of higher future cash flows, theory suggests that the stocks that comove with this MA are risky (because the MA surprise contains good news that lowers marginal utility). The implication is opposite to what we find: a positive risk premium for the long-short portfolio sorted on $\beta_{i,MKT}$. This result does not mean that MA surprises contain no information about future cash flows. Rather, it suggests that the cash flows news arriving through MAs is not what matters most to investors.[8] To clarify this point, we turn to the high-frequency expected cash flow series of Pettenuzzo, Sabbatucci, and Timmermann (2020). We find that various MA types significantly impact this series ($b_{CF,n}$ is large for some n). However, risk premia do not line up with these impacts: the portfolio sorted on aggregated exposures $\beta_{i,CF}$ (= $\sum_{n=1}^{N} \beta_{i,n} b_{CF,n}$) captures a small and insignificant CAPM α of -1.6% (t-stat= -0.9). Thus, our results present a challenge for models where the resolution of uncertainty about future cash flows drives the announcement day premium (see, e.g., Ai and Bansal, 2018). Under this premise, one would expect exposure to cash flow shocks to be an important driver of cross-sectional risk premia.

For discount rate risk to explain our results, it must be that news of higher discount rates is considered good news by investors (such that discount rates and marginal utility are negatively correlated). In this case, if an MAs positive price impact is due to news of lower discount rates, the stocks that comove with this MA are attractive as a hedge and should capture lower expected returns. In an ICAPM, the price of discount rate risk depends on whether the effect on lifetime utility of higher expected wealth growth outweighs the effect

[8]Similarly, our result does not mean that there is no MA type that contains news about cash flows that is priced in the cross-section. Rather, our claim is that this cannot be a general feature among the large set of MAs that we study.

of lower current wealth.[9] Our results thus provide support for models where the former effect – measuring the improvement in investment opportunities – dominates. Examples of such models include the ICAPM of Campbell (1996) when the coefficient of relative risk aversion is larger than one, and, under similar conditions, the ICAPM with reinvestment risk of Goncalves (2021a).[10] There is a striking analogy between our results and Goncalves (2021a), whose model explains the fact that long-term equity captures a negative CAPM α (see van Binsbergen and Koijen (2017) for a review). The idea is that long-term investors dislike reinvestment risk and long-term equity is attractive as a hedge against this risk. Short term equity takes out the long-term equity component from a position in the stock market, which increases reinvestment risk and therefore α. Similarly, subtracting our hedge portfolio from a position in the market increases reinvestment risk and thus α, because this strategy overweights stocks that comove with MAs that bring news of higher discount rates.

As noted in Kozak and Santosh (2020), the opposite prediction follows from some other specifications of the ICAPM as well as popular representative agent equilibrium models.[11] The intuition is that marginal utility correlates positively with discount rates, because the latter are high only in bad states. Although it is possible that our results only speak to the risk premium for exposure to discount rate news that comes out around MAs, these results

[9]Models often have implications for the price of risk for covariance, not beta, with discount rate news. Although these two may differ in the usual setting where monthly market returns are strongly negatively correlated with monthly discount rate news, our results identify the sign of the price of covariance risk. To see this, suppose that expected returns are determined by covariance with the market and a surprise S that aggregates MA surprises based on their impact on the stock market:

$$\begin{aligned} E(R_i) &= \gamma_M Cov(R_i, R_M) + \gamma_S Cov(R_i, R_S) \\ &= \lambda_M \beta_{i,M} + \lambda_S \beta_{i,S}, \end{aligned}$$

where $\lambda_S = \gamma_M Cov(R_M, R_S) + \gamma_S Var(R_S)$. Since $\gamma_M > 0$ and $Cov(R_M, R_S) > 0$, because MA surprises with the largest price impact get the largest weight in S, we have that λ_S can only be negative if γ_S is negative.

[10]The same prediction, that news of higher discount rates is a good state, obtains in models featuring some "irrational" investors, such as Campbell and Kyle (1993) and Barberis, Greenwood, Jin, and Shleifer (2015). In these models, a negative shock to sentiment that increases discount rates represents good news for the rational agents, because their investment opportunities have unambiguously improved.

[11]These alternative specifications of the ICAPM include Bansal, Kiku, Shaliastovich, and Yaron (2014) and Campbell, Giglio, Polk, and Turley (2018), who study heteroskedastic versions of the model in Campbell (1996). The equilibrium models include those with an external habit (e.g. Campbell and Cochrane (1999)), stochastic volatility (e.g., Bansal and Yaron (2004)) and time-varying risk aversion (e.g., Dew-Becker (2011) and Kozak (2022).

are critically important to discipline theories of asset prices around MAs.

Our in-sample tests show that two other components of MA news are also priced significantly. We find a positive risk premium for exposure to MA surprises that positively impact the short-rate and term spread. To the extent that monetary policy is a major cause of fluctuations in the short-rate, the former result is consistent with the stabilizer channel of monetary policy (expansionary policy is a response to bad shocks) and the empirical evidence in Ozdagli and Velikov (2020), in particular. The latter result is consistent with a large empirical literature that finds shocks to the term spread represent an improvement in consumption-investment opportunities.[12] These results come with an important caveat, however. The risk premia switch sign in the out-of-sample test, in which test the ex post exposure also drops considerably (especially compared to the stock market-news component discussed above). For the last news component we consider, the credit spread, risk premia are small in all of our tests. While this evidence could suggest this type of news is not important, we do note that both price impacts and exposures are relatively poorly estimated for this news component. If nothing else, these results mark the robustness of our evidence for the stock market-news component.

Our conclusions are robust in many dimensions. For instance, we allow price impacts to vary over time by conditioning on the Chicago Fed National Activity Index (similar to, e.g., McQueen and Roley, 1993; Boyd, Hu, and Jagannathan, 2005). Even though we find large and significant business cycle variation in price impact for a variety MA types, using conditional price impacts in our third stage yields by and large similar risk premia for the primitive news components. We also find similar results when we (i) expand the set of MA types, (ii) vary the set of firm characteristics used to estimate MA exposures, and (iii) aggregate exposures using a rank normalization of the price impacts $b_{k,n}$ that is more robust to outliers. As a by-product of our approach, we can also rank the characteristics on their importance for hedging each news component. For instance, we find that profitability is

[12]For instance, Adrian and Estrella (2008) find that a negative term spread has preceeded all US recessions since the 1950s. Further, Maio and Santa-Clara (2012) find that both the short-rate and the term spread predict stock market returns with a positive sign.

a key driver of exposure to the stock market-news component of MAs, whereas financial constraints are a key driver of exposure to the short rate-news component. Consistent with the idea that exposure to MA surprises is related to well-known firm characteristics, we find that the Fama and French (2015) five-factor model can partially explain the returns of our hedge portfolios.

To the best of our knowledge, we are the first to use price impacts to aggregate MAs at the news component-level. This approach contributes to various strands of the literature. Like Gilbert, Scotti, Strasser, and Vega (2017), a large number of pevious papers studies price impacts in bond markets.[13] Gilbert, Scotti, Strasser, and Vega (2017) argue that price impact is driven by timeliness and fundamentals, which is why price impacts are useful for aggregation. By giving large weight to the most timely and relevant MA types for each fundamental news component, we target these components in the estimation of MA risk premia. Like us, Boyd, Hu, and Jagannathan (2005) study stock price responses to MAs, but they focus only on unemployment news and do not estimate risk premia. Ozdagli and Velikov (2020) estimate the cross-sectional risk premium for a single MA: the FOMC announcement. Because this MA type is quite special (see footnote 4), our paper can be seen as a generalization of their approach. While the goal of Ozdagli and Velikov (2020) is to distinguish empirically between competing theories of monetary policy risk (see, also, Gürkaynak, Karasoy-Can, and Lee, 2022), our goal is to extract the primitive sources of information that any MA contains and estimate a risk premium for each of these sources.

We find that the news that matters most to investors is MA news that moves the aggregate stock market through changing discount rates. A large literature in asset pricing already estimates ICAPM representations of expected returns that include shocks to discount rates. For the largest part, this literature relies on the VAR-based approach introduced in Campbell (1991).[14] In a recent contribution, Kozak and Santosh (2020) use an asset's covariance with future realized market returns to estimate the exposure to discount rate shocks. Our paper

[13] See, e.g., Fleming and Remolona (1997), Balduzzi, Elton, and Green (2001), Goldberg and Leonard (2003), and Beechey and Wright (2009).

[14] See, for instance, Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Campbell, Giglio, Polk, and Turley (2018), and Koijen, Lustig, and Van Nieuwerburgh (2017).

is different because we focus on the discount rate news that comes out through MAs. The importance of discount rates is also highlighted in Chaudhry (2020), who presents causal evidence that MAs resolve uncertainty and the associated decrease in discount rates explains a significant part of the announcement day premium.

We finally contribute to literature that estimates the price of macroeconomic risk using low frequency betas with respect to innovations in macro-quantities (see, e.g., Ferson and Harvey (1991) and Chen, Roll, and Ross (1986) for the earliest work in this spirit). Herskovic, Moreira, and Muir (2019) find that these low frequency macro-betas are not priced. If the relevant macro-news comes out at much higher frequency around the MAs we study – in other words, if the signal-to-noise ratio is relatively large on MA days – it is perhaps unsurprising that we do find significant risk premia.

2. Data and methodology

Our main goal in this paper is to estimate risk premia for the primitive news components contained in MA surprises. In this section, we first introduce the MA types we study, which is a larger set than in most previous work. Indeed, our identification of risk premia comes from the cross-section of MA types and relies on three steps. First, we disentangle the primitive news components in MA surprises by estimating price impacts in bond and stock markets. Second, we estimate stock-specific risk exposures to all MA types. Third, we combine price impacts and exposures to estimate a risk premium for each primitive news component.

2.1 Macroeconomic announcements

Bloomberg provides economists' forecasts of MAs for our sample period starting late 1996 until early 2019. Our main analysis focuses on the top 25 announcement types with the highest Bloomberg relevance scores.[15] This score depends on the number of active alerts

[15] Although more than a hundred MA types are available in Bloomberg, many of these are only available over a short time series and their relevance is questionable. We show that our main results are robust to using a larger set of 46 announcements, which set contains all MAs studied by Gilbert, Scotti, Strasser, and Vega (2017) as well as those with Bloomberg relevance score exceeding 75.

that a particular MA type has on Bloomberg terminals, relative to alerts set for all US economic calendar events. Table I describes the set of 25 announcements we study. We see that nonfarm payroll, initial jobless claims and FOMC have the highest relevance scores. The 25 MA types we study have at least 13 years of data available and Bloomberg relevance scores larger than 84 (out of 100).

Some MA types, such as GDP and consumer sentiment, are decomposed into preliminary, advance, and final releases, where the preliminary announcements are updated in the advance and final stages. Following Gilbert, Scotti, Strasser, and Vega (2017), we consider each of these series as a separate indicator. If this structure causes one of these releases to have a particularly large price impact, our approach will assign a larger weight to this release when we estimate risk premia. Similarly, if the announcement window of two types is overlapping, the earlier announcement may have larger price impact and therefore receive a larger weight when we estimate risk premia. If two announcements happen on the same day, they may capture the same news and we may end up overweighting this news.[16] If this news is irrelevant, it will bias our risk premia estimates towards zero. If this news is relevant, our risk premia estimates may be biased towards the news content of these MA types. For this reason exactly, we show in a robustness check that our results are robust to alternative weighting schemes and we perform a bootstrap simulation to analyze the sensitivity of our results to overlapping announcements.

We measure the surprise $S_{n,d}$ in MA type n on day d as the actual release minus the median forecast:

$$S_{n,d} = \frac{Actual_{n,d} - Med(Forecast)_{n,d}}{\sigma_{S_n}}, \tag{1}$$

where we divide by the standard deviation of this difference to make announcement types comparable.[17] Forecasts are made starting one to two weeks before a release and are updated

[16] The days in our sample (5606 in total) are roughly equally divided between days with no MA (1975), days with a single MA (1721), and days with two or more MAs (1910). Within the last group, two or three MAs are most common (1281 and 503 days, respectively).

[17] In in-sample tests, we use the full sample to standardize the surprises; in out-of-sample tests, we use only the sample up to day d to standardize the surprises.

in real time up to the night before the release. For every announcement, we observe the latest forecast made by each economist and we use on average about 60 forecasters per announcement.

Following previous literature, we treat FOMC surprises differently than other MA types. Analysts often correctly anticipate changes in target rates, especially after interest rates reach the zero lower bound in December 2008. Despite this anticipation, FOMC announcements significantly impact financial markets, because their importance does not lie exclusively in the new target rate, but also in the so-called "Fed speak" that surrounds it. The latter reveals valuable information about the future path of target rates. We follow Gürkaynak, Sack, and Swanson (2005a) and Gertler and Karadi (2015) and identify FOMC surprises and news about the future path using high frequency data in tight windows around FOMC announcements.[18] In particular, the target factor is the 30 minute window change in current month's Fed Funds futures (adjusted for the day of the release); the path factor is the second principal component of the set of tight window changes in federal funds futures and Euro-Dollar futures with a maturity up to one year. The sample for FOMC target surprises is from February 1994 to June 2008, to exclude the zero lower bound period, and for FOMC path surprises it is from February 1994 to January 2019. We exclude FOMC surprises prior to 1994 because monetary policy decisions were not explicitly announced (Gürkaynak, Sack, and Swanson (2005a)).

2.2 Price impact of surprises

Our prime interest lies in the relation between price impacts and risk premia across MA types. We consider the price impact of each MA type n on day d in four major asset classes k (the "news components" discussed before), including the short-term rate (one-year US Treasury bond yield), the term spread (the ten-minus-one year yield difference), the credit spread (the difference between the BAA-rated corporate bond yield and the ten year yield)

[18] We thank Bauer, Lakdawala, and Müller (2021) for sharing data on 30 minute window changes in futures rates.

and, finally, excess stock returns.[19] We estimate the price impacts $b_{n,k}$ using a regression of short-window changes in yields $y_{k,d}$ (roughly proportional to the inverse of bond returns) and cumulative excess stock returns $R_{k,d}$ on the surprises:

$$\Delta y_{k,d:d+2} = a_{k,n} + b_{k,n} S_{n,d} + \epsilon_{k,d:d+2} \quad \text{for yields} \quad (k = 1:3), \text{and} \tag{2}$$

$$R_{d:d+2} = a_{k,n} + b_{k,n} S_{n,d} + \epsilon_{k,d:d+2} \quad \text{for excess stock returns} \quad (k = 4). \tag{3}$$

We choose to measure price impact over a three-day window (from the end of day $d-1$ before the announcement to the end of day $d+2$) to be consistent with how we measure exposures to MA surprises at the individual stock-level (see Section 2.3 for more detail). Similar to us, Gürkaynak, Karasoy-Can, and Lee (2022) use a two-day window to estimate how exposure to FOMC path surprises varies in the cross-section. We show in a robustness check that our main results are robust to estimating price impacts using only the announcement day. The advantage of studying a longer window is that investors have more time to process the unknown information bundle contained in the MA, which is the first major reason why, in practice, MA news will be incorporated into prices with a delay. The second major reason for a delay is that even if investors could immediately process the information, they would face liquidity challenges when trading on it. These liquidity challenges can be serious, especially in the cross section of stocks. For instance, Boguth, Grégoire, and Martineau (2019) show that the SP500 futures market - which is incredibly liquid relative to the market for a typical stock - is subject to large price pressures in the first hours after FOMC announcements. As a result of these price pressures, price informativeness can be low for the aggregate stock market in the shortest windows. Of course, if the true effect of MAs is present at higher frequencies, the disadvantages of studying a longer window are noise and confounding factors. If we are merely adding noise, our results - which are strongly statistically significant – present a lower bound on the true effect. The fact that we study a large set of MAs alleviates the concern of

[19] We choose these four news components because they broadly make up a stock's expected return: the short-term (risk-free) rate, a term spread because stocks are long duration assets, a credit spread because stocks are issued by firms that can go bankrupt, and finally a component compensating for equity-specific risks. All yield data are downloaded from FRED; the stock market return is from Kenneth French's website.

confounding factors. Indeed, for a confounding factor to drive our results it must not only bias the price impacts, but it must also show up accordingly in cross-sectional risk premia.

In our empirical work, we focus on recursively orthogonalized yield changes and returns. For instance, when we estimate the price impact in the stock market, the daily stock market return is orthogonalized from changes in the short-term rate, term spread, and credit spread (using all days in our sample period). This approach alleviates the concern that a price impact in the stock market may partly be due to an impact on discount rate components that are not unique to equities (e.g., equities are long-term assets and therefore also sensitive to news about long-term bond rates). We show that our results are robust to not orthogonalizing. We report the price impacts on all four news components for all 25 MA types in Table OA.1 of the Online Appendix.

2.3 Risk exposures

To estimate risk premia, we need to differentiate stocks on their exposures to the different MA types we study. To this end, we obtain daily and monthly stock return data from CRSP and additional accounting data to construct firm characteristics from Compustat.[20] We broadly estimate two types of exposures for each firm. Our first estimate of a firm's exposure is in-sample and defined as a linear combination of firm characteristics. Our second estimate of a firm's exposure is estimated using expanding window regressions of MA day returns on MA surprises. Although these exposures are likely to be more noisy than the characteristic-based exposures, the advantage is that we use no forward-looking information.

The characteristic-based methodology was introduced in the asset pricing literature by Pastor and Stambaugh (2003) in a different setting, but it has been used in a setting similar to ours by Ozdagli and Velikov (2020) and Gürkaynak, Karasoy-Can, and Lee (2022). The basic premise of this approach is that priced firm characteristics must pick up variation in true underlying sources of risk under the null of popular multi-factor models, like the ICAPM

[20]We include only stocks with share codes 10 and 11 and those that are traded on the NYSE/NYSE MKT/NASDAQ/ARCA. We drop financial firms (SIC codes between 6000 and 6999), utility firms (SIC codes between 4900 and 4999) and penny stocks.

and APT. Moreover, as noted in Ozdagli and Velikov (2020), economic theories provide guidance for the set of firm characteristics that should capture variation in exposures in a MA setting. For instance, discount rate news has a larger effect on firms with longer investment horizons, cash flow duration, cash flow uncertainty and firms that rely more heavily on external financing. In contrast, sticky price and wage models predict that cash flow news is more important for low profitability firms (with revenues close to input costs).

Based on these insights, we focus on a set of nine characteristics that combines the five characteristics studied in Ozdagli and Velikov (2020) with four standard characteristics used in the Fama and French (1993) and Fama and French (2015) models. The characteristics of Ozdagli and Velikov (2020) are the Whited and Wu (2006) financial constraints index, cash, cash-flow duration (see Weber (2018)), cash flow volatility, and operating profitability, which we construct exactly as described in their Appendix A.1. The standard characteristics are market beta, size, book-to-market ratio, and investment.[21] We include market beta as a control, because we find that exposures to some of the MA types we study correlate strongly with market beta. Effectively, we subtract out the variation in exposures due to market beta when computing the firm-specific exposures to MA surprises that we use to form our hedge portfolios.[22] We show in Section 4.5 that our results are robust to not controlling for market beta, which is the approach followed in Ozdagli and Velikov (2020).

More specifically, over the full sample period for which we have MA surprises available and for each MA type n, we run a panel regression of three-day cumulative individual stock returns on firm characteristics, the interaction between surprises and firm characteristics, and a number of fixed effects:

$$r_{i,d(t):d(t)+2} = \alpha^n + \Sigma_{c=1}^{9}\beta_c^n X_{i,t-1}^c + \Sigma_{c=1}^{9}\gamma_c^n S_{n,d(t)} X_{i,t-1}^c + \mu_i^n + \mu_{d(t)}^n + \mu_{i(j)}^n + \epsilon_{i,d(t):d(t)+2,n}, \quad (4)$$

[21]The book value for the book-to-market ratio is defined as in Davis, Fama, and French (2000) and the market value is updated monthly. Investment is defined as the annual %-change in total assets.

[22]The idea is analogous to Herskovic, Moreira, and Muir (2019): we want to construct a hedge portfolio that when added to a unit investment in the aggregate stock market eliminates as much as possible of the stock market price impact of MA surprises. While this price impact can obviously be eliminated by not investing in the stock market at all, this portfolio choice is infeasible for most real-world investors.

where $d(t)$ is the day d in month t that announcement type n is released, i is a firm indicator, and $X_{i,t-1}$ is the set of nine firm characteristics observed at the end of month $t-1$.[23] We take into account a two-quarter reporting lag in accounting data for the observation of the firm characteristics. We estimate this regression using weighted least squares, weighting each observation with the natural logarithm of the corresponding firm's market capitalization, to control for the skewness of firm size in our sample. We include fixed effects for firms μ_i^n, announcement days $\mu_{d(t)}^n$, and industries $\mu_{i(j)}^n$ (based on Fama and French's classification in $j = 1, ..., 48$ industries).

Using the estimates from this regression, we have that a firm's conditional exposure (net of exposure coming from market beta) to MA type n in each month t equals: $\beta_{i,n,t}^X = \Sigma_{c=1}^8 \hat{\gamma}_c^n X_{i,t-1}^c$. An advantage of this approach is that the full cross-section of stocks is used to estimate the functional form of conditional exposure to MA surprises, which reduces noise relative to running time series regressions of firm returns on surprises. Another advantage is that we can backdate firm-exposures to as early as 1977 (when all nine firm characteristics are available for a sufficiently large number of firms) by combining the γ_c^n estimates from Equation (4) with firm characteristics observed prior to the period when we observe MA surprises. This backdating procedure provides us with a much longer time-series of exposures, which allows us to estimate risk premia more precisely. Another advantage of this backdating procedure is that it provides us with an alternative "historical" estimate of risk premia. These alternative risk premia are calculated over the pre-announcement period from 1977 to 1994.[24]

The second, out-of-sample method to estimate a firm's exposure to MA risk relies on running the price impact regression of Equation (4) at the individual firm-level over an

[23]We standardize firm characteristics every month for interpretability and winsorize them at the 2.5%-level.

[24]Note that some of the characteristics we study, like the Whited-Wu financial constraints index and duration, are constructed as a function of other underlying characteristics. This function is estimated using full sample information. Thus, estimating the pooled regression of Equation 4 over an expanding window should not be seen as a truly out-of-sample exercise. That said, we show in a robustness check that this exercise generates similar results as the truly out-of-sample exercise we discuss next.

expanding historical window:

$$R_{i,d(\tau):d(\tau)+2} = a_{i,n} + \beta^{EW}_{i,n,t} S_{n,d(\tau)} + \beta_{i,MKT,t} R_{MKT,d(\tau):d(\tau)+2} + \epsilon_{i,d(\tau):d(\tau)+2}, \text{where } \tau = 1 : t-1. \tag{5}$$

Here, (i) $\beta^{EW}_{i,n,t}$ is the firm's conditional exposure estimated using only announcements up to and including month $t-1$ and (ii) we control for exposure to the market, as we do in the characteristic-based approach. We estimate the exposure for any firm i that has return observations available for at least five years of announcements (requiring that the return may not be missing for the latest announcement prior to month t) and winsorize these exposures at the 2.5%-level (just like the firm characteristics).

2.4 Estimating risk premia by aggregating risk exposures

With these exposures in hand, we could estimate the risk premium for each MA type n. A standard way to do so would be to construct a long-short hedge portfolio by sorting stocks on the estimated $\beta_{i,n,t}$.[25] These risk premia are hard to interpret, however. The reason is that each MA type bundles unknown quantities of different news components, that is, news relevant to price risk-free bonds, risky bonds, and stocks (affecting their discount rates or cash flows, or both). Aggregating across MA types allows us to estimate a risk premium for each of these primitive news components. Under the null that these components ultimately represent the risks that matter to investors, sorting stocks on the exposures to a single announcement is suboptimal. Intuitively, stocks would be allocated to the wrong portfolio, thus reducing the variation in risk premia across portfolios. Under this null, the more powerful test is to sort on an aggregated exposure that uses the relative quantities of the news components in each MA type.

For this reason and to test whether exposure to a news component k is priced, we will

[25] We present risk premia (using characteristic-based exposures) for such standard MA hedge portfolios in Table OA.1.

sort stocks on:

$$\beta^{X}_{i,k,t} = \sum_{n=1:N} \beta^{X}_{i,n,t} b_{n,k} \tag{6}$$

$$\beta^{EW}_{i,k,t} = \sum_{n=1:N} \beta^{EW}_{i,n,t} b_{n,k,t}, \tag{7}$$

that is, a weighted average of the exposures $\beta_{i,n,t}$ from Equations (4) and (5) that uses the price impacts from Equations (2) and (3) as weights.[26] In Equation (7), we aggregate using price impacts estimated over an expanding window to ensure we use no forward-looking information. This choice has little impact on our results, however. Finally, note that aggregating exposures is attractive also because noise in the estimated betas $\beta_{i,n,t}$ may cancel out.

With the aggregated conditional exposures $\beta_{i,k,t}$ in hand, we sort stocks into value-weighted quintile portfolios using NYSE breakpoints. Then, the return in month t of the hedge portfolio for news component k is the return of the portfolio that goes long the high-exposure quintile and short the low-exposure quintile. Our main measure of the risk premium for each news component k is the CAPM α of this long-short portfolio. We focus on the CAPM α for three reasons. First, previous literature has already shown that aggregate stock market returns are somewhat extraordinary on announcement days. We want to control for this fact, which is a concern if our long-short portfolio does not turn out to be exactly market-neutral ex post. Second, in many theoretical asset pricing models, the market is the first factor and sufficient information to identify an additional risk factor is the CAPM α. For instance, in the ICAPM, exposure to variables that capture shocks to the investment opportunity set (which is what the MA surprises effectively are) is priced, over and on top of exposure to the market. Third, the CAPM α speaks directly to the improvement in portfolio Sharpe ratio when an investment in the market is combined with a position in our long-short portfolio that aims to hedge MA risk. When we estimate αs relative to larger factor models

[26] We rank-normalize the exposures $\beta_{i,n,t}$ to the interval $[0, 1]$ for each MA type n to make them more comparable and to reduce noise. We show in a robustness check that our main conclusion is not sensitive to this transformation. To alleviate the concern that the largest price impacts $b_{n,k}$ may be poorly estimated, we also use rank-normalized price impact weights in a robustness check.

in a robustness check, these regressions will be interesting also to determine which factors load most strongly on MA risk. Indeed, if characteristics are important determinants of MA exposure, one would expect the risk premia of characteristic-based factors to be consistent with compensation for MA risk.

We could alternatively construct news component-specific hedge portfolios by sorting stocks on their exposure to each news component k in a short window after the MAs. In fact, it seems plausible that these exposures are easier to estimate than the exposures to MA surprises. However, MA surprises generally only explain a small fraction of the changes in yields and stock returns in the three-day window around MAs. In particular, Table OA.1 shows that the R^2 in the price impact regressions of Equations (2) and (3) is rarely over 5%. Table OA.2 shows that this result extends to a tighter one-day window. Hence, sorting stocks on these "direct" exposures to the news components is tantamount to sorting on co-variation that is orthogonal to the MA surprise and thus would not be informative about the price of MA risk.

3. Main results

In this section, we present our main results that link price impacts of MA surprises to cross-sectional risk premia on portfolios that hedge against these surprises.

3.1 Price Impacts

We present the estimated price impacts (see Equations (2) and (3)) on each news component and for each of the 25 MAs in Table OA.1 of the Internet Appendix. Table II lists the MAs that generate the three largest positive and negative impacts over our full sample period. Let us start with the main insight that broadly motivates our approach: there is wide dispersion in the top MAs across news components. For instance, among the 24 MAs with the largest impacts, 14 are unique. Only two MA types are mentioned three times: FOMC target and Michigan sentiment. We thus conclude that different MAs impact different news components and studying few MAs – as is commonly done in the literature – ignores important news. Furthermore, the magnitude and sign of price impacts varies strongly across MAs. We use this measure of the "content" of MAs – ignored in the recent literature on the announcement day premium – to sign and weight the large set of 25 MAs when we estimate a stock's exposure to the different components of MA news.[27] This approach increases precision of the estimated MA risk premia, when it is this smaller set of news components that ultimately matters to investors.

Let us now discuss the evidence for each news component. We find that the short-term rate responds most strongly to the non-farm payroll, ISM manufacturing and retail sales announcements. Quantitatively, these impacts are large. For instance, the estimates of about 0.025 for the top 3 positive MAs imply that the one-year Treasury bond yield increases by 2.5 basis points for surprises of one standard deviation magnitude. This increase represents 36% of the unconditional standard deviation in three-day yield changes. Gilbert, Scotti, Strasser, and Vega (2017) estimate similar price impacts for Treasury yields with maturities up to five years over a slightly shorter sample period.

We find that the term spread is most sensitive to the FOMC path and advance retail sales announcements. Quantitatively, we find that the term spread increases by about 1.6 basis points for surprises of one standard deviation magnitude. This increase represents 20% of the unconditional standard deviation in three-day term spread changes. These impacts are consistent with Gürkaynak, Sack, and Swanson (2005a), who argue that most of the variation in long-term interest rates are related to the path factor rather than changes in the target federal funds rate (FOMC target), and Gürkaynak, Sack, and Swanson (2005b), who find that output indicators (e.g. advance retail sales) have a large and positive impact on the term spread.

The credit spread responds most strongly to the industrial production and University of Michigan sentiment announcements. We find that the credit spread drops by 1.6 and

[27] Some of the estimated price impact coefficients have large standard errors. If these estimates represent pure noise, this would bias against finding a risk premium when we use these coefficients to aggregate exposures up to the news component level. Relatedly, the bootstrap experiment we present below alleviates the concern that our results are driven by a few influential observations for specific MA types.

0.8 basis points, respectively, for a one standard deviation surprise. These drops translate to 35% and 17%, respectively, of the unconditional standard deviation in three-day credit spread changes. The signs of these price impacts are consistent with the idea that credit spreads are negatively related to macroeconomic activity (see, e.g., Chen, 1991; Gilchrist and Zakrajsek, 2012; Boons, 2016) and sentiment that may in fact respond to uncertainty about future macroeconomic growth (Tang and Yan (2010)).

Finally, announcements about the path of future interest rates (FOMC path) and monthly figures about changes in non-farm private sector employment (ADP employment change) have the largest impact on the stock market. The three-day cumulative excess stock market return increases by 46 basis points (drops by 53 basis points) for a positive one standard deviation surprise in ADP employment (FOMC path). These changes are large and represent 25% (29%) of the unconditional standard deviation in three-day cumulative stock market returns. The positive impact of ADP employment is consistent with the idea that an increase in jobs created is an indicator of future economic growth. The result for FOMC path is consistent with the evidence in Gürkaynak, Sack, and Swanson (2005a) and the idea that discount rates increase as monetary policy tightens (see the evidence for the term spread above).

Of course, the fact that a large variety of MAs generate large price impacts in these major news components is unsurprising from the perspective that professionals closely follow these MAs (as can be seen from the Bloomberg relevance scores). The table also shows that different variants of the same announcement category are important for different targets. For instance, employment news affects the short-term rate via initial jobless claims and non-farm payroll, while the credit spread and stock market respond to changes in ADP employment.[28] This fact underscores the importance of studying the cross-section of MAs rather than focusing on one particular type of announcement. We also find that preliminary or advanced announcements are often more important than final realizations (see, e.g., preliminary sen-

[28]Due to variation in timing, coverage of the underlying employment measure, or analyst forecast performance, it may well be that different employment surprises are differentially correlated to the fundamental variables that drive the valuation of the assets we study (see, also, Gilbert, Scotti, Strasser, and Vega, 2017).

timent and GDP). This fact may help explain the puzzling evidence in Herskovic, Moreira, and Muir (2019). These authors show that exposure to low-frequency changes in realized macro-variables (such as innovations in monthly industrial production) is not compensated with a risk premium. A portfolio that is exposed to final realizations may carry a low risk premium because it does not hedge the shocks that change investor expectations already prior to the final release. We capture the true shocks better using preliminary or advance announcements and conditioning on analysts' forecasts.

3.2 Risk premia

Table III presents our main result, that is, the risk premium for exposure to each news component k. Recall from Section 2.4 that these risk premia are estimated as the CAPM α of a value-weighted long-short quintile portfolio sorted on exposures to MA surprises aggregated at the news component-level (denoted $\beta_{i,k}$, see Equations 6 and 7). Panel A reports risk premia for the full sample from 1977 to 2019, with characteristic-based exposures estimated in-sample. Panel B reports our measure of risk premia that focuses only on the period with backdated exposures based on firm characteristics in the pre-announcement sample (from 1977 to 1994). Panel C reports our "out-of-sample" measure of risk premia estimated over the period 2002 to 2019 and using exposures that are estimated over expanding windows starting the first day an MA type enters our sample.

The single most robust finding in this table is the negative risk premium for exposure to MA types that impact the stock market. The magnitude of the α (annualized) of the high-minus-low exposure portfolio is economically and statistically large: ranging from -8.04% with a t-statistic of -4.89 (using characteristic-based in-sample exposures) to -4.85% with a t-statistic of -2.46 (using expanding window-based out-of-sample exposures). Thus, firms that are more (less) sensitive to MA surprises n that have a positive impact on the stock market earn lower (higher) risk-adjusted returns.

An investor in the stock market who wants to hedge against the stock market price impact of MA surprises should short the high-minus-low portfolio. The large and significant negative α of this portfolio implies that the investor will substantially increase her Sharpe ratio. To see this, consider combining a 1$ investment in the market with a -1$ investment in the portfolio. In the full sample, the average return of this strategy is 12.73% and the Sharpe ratio equals 0.91. This represents a huge improvement over investing only in the market, which provides a return of 7.69% and a Sharpe ratio of 0.50. This improvement is robust out-of-sample at a return of 10.98% and a Sharpe ratio of 0.76 for the hedged strategy and a return of 7.39% and a Sharpe ratio of 0.51 when investing only in the market. Thus, provided that the portfolio also hedges ex post (as confirmed in the next section), we must conclude that MA surprises that impact the stock market can be hedged without giving up return.

To understand this surprising result, note in the last column of Table III that our hedge portfolio is exposed to the stock market. The unconditional monthly β equals 0.39 (0.17) in the in-sample (out-of-sample) test. In a CAPM world, this β would imply a vastly different return than what we find in the data. This finding suggest that the particular component of the market return on which our hedge portfolio loads relatively strongly - the stock market price impact of MAs - is priced differently than other components of the market return. Hence, it is key to consider the asset pricing implications if this price impact were driven either by aggregate cash flow or discount rate news captured by MA surprises.

Recall, we find that firms that are more (less) sensitive to MA surprises n that have a positive impact on the stock market capture lower (higher) risk premia. If this positive impact were due to news of higher future cash flows, stocks exposed to these surprises are risky and theory would suggest that they command higher risk premia (the returns of these stocks correlate negatively with marginal utility, because they pay off when cash flow news is good). This prediction is opposite to what we find in the data. Therefore, we conclude that the cross-sectional risk premium for exposure to MA surprises that impact the stock market is not driven by the cash flow news these surprises contain.

If the positive impact of MA surprise n on the stock market were due to news of lower discount rates, the risk premium will depend on whether investors consider higher or lower discount rates bad news. In the ICAPM, the price of discount rate risk depends on whether the effect on lifetime utility of higher expected wealth growth outweighs the effect of lower current wealth. If the former effect is stronger, news of a lower discount rate (expected return) is considered bad news by the agent that increases marginal utility. In this case, the risk premium for covariance with a MA surprise n that contains discount rate news that increases aggregate stock prices, is negative, because such stocks are attractive to hedge against changes in investment opportunities. However, as noted already in Kozak and Santosh (2020), a large variety of representative agent equilibrium models in the literature would actually suggest that low discount rates are a symptom of a being in a good state, in which case discount rates covary positively with marginal utility. We conclude that the hedged strategy discussed above generates such a large Sharpe ratio, because it is very risky: the strategy adds to the market a long position in stocks that carry a lot of reinvestment risk as they pay off when MA surprises contain news of increasing discount rates.

In the tests that use characteristic-based exposures, two other components of MA news are also priced significantly. The risk premia for exposure to MA surprises that positively impact the short-rate and term spread are positive over the full sample (at an annualized 3.48% and 5.52%, respectively; Panel A) as well as in the pre-announcement sample (at 5.28% and 7.20%, respectively; Panel B). This result suggests that investors command a premium to be willing to invest in stocks that pay off when MA surprises lead to an increase in the level and slope of the term structure. To the extent that monetary policy is a major cause of fluctuations in the short-rate, the former result is consistent with the stabilizer channel of monetary policy (see Ozdagli and Velikov, 2020). The latter result is consistent with a large empirical literature that finds shocks to the term spread represent an improvement in consumption-investment opportunities. For instance, Adrian and Estrella (2008) find that a negative term spread has preceeded all US recessions since the 1950s. That said, these risk premia switch sign in the out-of-sample test using expanding window exposures (Panel C). In this test, the risk premium for the short-rate is even significant at -2.4%. For the last news component we consider, the credit spread, risk premia are small and insignificant in all three panels.

An aggressive interpretation of the results so far is that for the typical announcement – among the 25 we study – it is news moving stock prices that matters most to investors. A more conservative interpretation acknowledges that stock's MA exposures are noisy and hard to estimate, which may drive a wedge between ex-ante and ex-post exposures. This is particularly true for the expanding window exposures, which is the exact exercise that generates contradictory evidence for the short-rate and term spread. Therefore, it is important to ensure that the long-short portfolios we construct are exposed ex post to the MAs that contain the most relevant information for each news component. We turn to this question next.

3.3 Ex-post exposures

An important condition to interpret the CAPM α of the long-short portfolio as a compensation for risk is that this portfolio hedges ex-post. In our setting, this would mean that the returns of the portfolio sorted on exposures aggregated at the level of news component k hedge MA surprises that impact this particular news component.

To test this implication, we run a pooled regression of three-day returns on the long-short portfolio for news component k, $R_{k,d:d+2,n}$, on announcement surprises $S_{n,d}$ that we weight by their estimated price impact $\widehat{b_{n,k}}$:

$$R_{k,d:d+2,n} = \alpha_n + \beta(\widehat{b_{n,k}} S_{n,d}) + \epsilon_{k,d:d+2,n}. \tag{8}$$

The unit of observation is an announcement day d of MA type n and we pool all days and types. We include MA type fixed effects and cluster standard errors at the monthly level, because the three-day windows may overlap across different MA types.

This regression is interesting for at least two reasons. First, it directly asks whether a single monthly rebalanced portfolio is able hedge the relevant components of MA news that arrive at a higher frequency and through multiple MA types within the month. Second, it is straightforward to gauge how successful the hedge is, because the benchmark for the coefficient estimate $\beta = 1$. This benchmark estimate obtains when we run this regression substituting on the left hand side the news component (e.g., three-day changes in the term spread or stock market returns; see Equations (2) and (3)). In order to make the exposure of the high-minus-low hedge portfolio, which is a portfolio of stocks, comparable to the exposure of the news components k, which include changes in yields, we rescale each hedge portfolio to have the same volatility as the corresponding news component. We present coefficient estimates β from these regressions in Table IV.

In the first rows of the table, we present the benchmark coefficient estimate, which is strongly significant. This finding indicates that each news component k is significantly exposed to MA surprises that strongly impact this news component. We next report results for the long-short portfolios that are constructed using, respectively, characteristic-based exposures (in-sample) and expanding window exposures (out-of-sample). The former exercise is interesting as a full information benchmark as it allows us to gauge how much worse a portfolio will hedge when it is constructed in real-time. For the full information benchmark, we find that the exposures are significant for three out of four news components, ranging from 0.22 (t-stat= 2.47) for the short rate to 0.52 (t-stat= 3.42) for the aggregate stock market. The exposure is relatively small and insignificant for the credit spread. Interestingly, the exposures do not drop much when no forward-looking information is used in the construction of the hedge portfolios. Indeed, for the hedge portfolio constructed using expanding window betas, the ex-post exposure remains about 0.25 for the short rate and term spread and it is still the largest and significant for the stock market at 0.41 (t-stat= 2.00). This result means that about 41% of the price impact of MAs in the stock market will be eliminated when a position in the stock market is combined with a short position in the hedge portfolio. Overall, we conclude that three out of four MA news components can be hedged even in real-time. These large ex-post exposures strengthen our case that investors are willing to pay a premium to invest in these portfolios.[29]

[29]Following this line of reasoning, it may well be that the risk premium for the credit spread-news component is small because we are not able to construct a portfolio that is truly exposed to MA types that contain

Note that the ex post hedging potential for the stock market-news component is large even compared to the market β of this portfolio (0.41 versus 0.17, see Table III). Naturally, investors can also reduce their exposure to the stock market impact of MAs by moving part of their investment in the market to the risk-free asset. However, this alternative hedging strategy will lower the portfolio's expected return, while leaving the Sharpe ratio unchanged. Our hedge portfolio is able to eliminate 41% of the stock market impact of MAs, while actually increasing the return and Sharpe ratio.

In order to shed more light on the type of MAs that the hedge portfolios are exposed to, Table V reports the exposures of the hedge portfolios to the MA types with the largest positive and negative price impacts for each news component (see Table II). To estimate these exposures, we proceed as in Equation (8) but include only the relevant subset of two (top and bottom), four (top 2 and bottom 2) and six (top 3 and bottom 3) MA types n.

Focusing on the stock market-news component, the evidence confirms the idea that the hedge portfolio earns a large premium because it hedges the most relevant MA types with the largest price impacts on the stock market. In the out-of-sample test, about 77% of the price impact of the top and bottom MA types (ADP employment and FOMC path) can be eliminated by the hedge portfolio. This hedge ratio is about 53% for the top and bottom two MA types and converges to about 39% when we go to the top and bottom three, which number is similar to what we find when we include all MA types in the regression. For the other news components, we find that only the short-term rate hedge portfolio is significantly exposed ex-post to the top announcements (the hedge ratio decreases from about 50% to 30% going from the top and bottom MAs to the top and bottom three).

4. Additional analyses

In this section, we extend our results in a variety of dimensions to deepen our understanding of the determinants of the MA risk premia we estimate in the previous section and to show robustness.

such news.

4.1 Cash flow news

As discussed in Section 3.2, the fact that the risk premium for the stock market-news component is negative invalidates a story based on cash flow news. This is not to say that there is no cash flow news arriving through MA surprises. Rather, it means that risk premia in the cross-section of equities do not line up with exposure to MA surprises that impact the stock market because of the cash flow news they contain. Unfortunately, we are not aware of a daily decomposition of stock market returns into cash flow and discount rate news for our full sample period. Therefore, we will use the high frequency expected dividend growth series of Pettenuzzo, Sabbatucci, and Timmermann (2020), which the authors argue to be highly correlated to the cash flow news from such a daily decomposition.

To be precise, Pettenuzzo, Sabbatucci, and Timmermann (2020) filter the persistent component of the expected dividend growth series, where dividend growth is measured as the year-over-year change in the sum-total of dividends announced by the same set of firms in the same fiscal quarters:

$$G_t = \frac{\Sigma_{i=1}^{N_t} I_t^i D_t^i}{\Sigma_{i=1}^{N_t} I_{\tilde{t}}^i D_{\tilde{t}}^i}, \tag{9}$$

where I_t^i is an indicator that firm i announces dividend D_t^i on day t, and $\tilde{t}$ is the dividend announcement day in the same quarter of the previous year. The authors then provide the following structural time-series decomposition of the dividend growth process $\Delta d_{t+1} = log(G_t)$:

$$\Delta d_{t+1} = \mu_{d_{t+1}} + \xi_{d_{t+1}} J_{d_{t+1}} + \epsilon_{d_{t+1}}, \tag{10}$$

where $\xi_{d_{t+1}} J_{d_{t+1}}$ is a jump component, $\epsilon_{d_{t+1}}$ is a cash flow shock term with time-varying volatility, and $\mu_{d_{t+1}}$ is the persistent component of the dividend growth process that the authors model as an $AR(1)$ process:

$$\mu_{d_{t+1}} = \mu_d + \phi_{d_{t+1}} (\mu_{d_t} - \mu_d) + \sigma_\mu \epsilon_{\mu_{t+1}}, \text{ where } \epsilon_{\mu_{t+1}} \sim N(0,1) \tag{11}$$

As explained in detail in their Internet Appendix, the authors adopt a Bayesian approach that uses Gibbs sampling to estimate the model parameters and filter the smoothly evolving mean $\mu_{d_{t+1}}$. We thank the authors for sharing the latter time series on their website.

First, we show in Table OA.3 of the Internet appendix that various MA types have a significant impact (measured in the three-day window around an announcement) on expected dividend growth. For instance, retail sales (unemployment) has the largest positive (negative) impact, consistent with the idea that higher real activity ultimately leads to higher dividends (see, e.g., Boyd, Hu, and Jagannathan, 2005). Next, we ask whether risk premia line up with an aggregated exposure to MA surprises (see Equations 6 and 7), where we now aggregate using the impacts on the expected dividend growth series. We sort stocks on this aggregated exposure as in Table III and present the CAPM α of the long-short quintile portfolio in Table VI.

Independent of whether we use characteristic-based or expanding window exposures to MAs, we find small and statistically insignificant risk premia for this cash flow news component of MA surprises. If anything, the risk premium is negative, just like in Table III, which is inconsistent with the standard notion that investors command a premium to invest in stocks that comove with MA surprises that imply an increase in expected future cash flows. Note that the relevance of cash flow news is an important premise of models where the resolution of uncertainty about future cash flow growth drives the large and positive average stock market return on announcement days (Ai and Bansal, 2018). Our results suggest that – on average across our set of announcements – the cash flow news that arrives through MA surprises is not something that is priced in the cross-section.

Under the assumption that changes in the expected dividend growth series are a good proxy for cash flow news, the absence of a strong relation between impacts on expected dividend growth and risk premia implies the presence of a strong relation between impacts on discount rates and risk premia. In fact, given that the stock market return is the sum of these two components, the relation between impacts on discount rates and risk premia should be even stronger than what we find in Table III. In this sense, our results present only a lower bound on the asset pricing relevance of discount rate news that arrives through

MA surprises.

4.2 Which characteristics drive our results?

We next examine the characteristics of stocks that form our hedge portfolios. More precisely, we run pooled regressions of the rank-transformed exposures aggregated at the news component-level (see Equations (6) and (7)) on the firm characteristics:[30]

$$\beta_{i,k,t} = a^k + \Sigma_{c=1}^{8} \gamma_c^k X_{i,t-1}^c + \mu_i^k + \mu_{i(j)}^k + e_{i,k,t}, \tag{12}$$

where we include firm and industry fixed effects as in Equation (4). Table VII reports the estimated loadings γ_c^k. Panel A presents results for exposures estimated in-sample as a function of characteristics (see Equation (4)); Panel B presents results for the exposures estimated over an expanding window (see Equation (5)). Since the exposures in Panel A are (approximately) a linear combination of the characteristics used in regression (12), there is no need to test significance. Rather, our interest is in the relative magnitude of the loadings at the news-component level, which are directly comparable because the characteristics are standardized. Panel B is interesting because it provides for an out-of-sample test of the hypothesis that firm characteristics capture variation in exposure to MA surprises.

First and foremost, there is interesting variation across news components in the most important characteristics, consistent with the idea that different characteristics capture exposure to different types of news. Let us discuss some characteristics that are consistent in sign between the two panels. For instance, the Whited and Wu (2006) financial constraints index is an important characteristic for the short rate-news component with the 2nd largest coefficient in both panels. The negative loading on the financial constraints index suggests that the long-short portfolio is short financially constrained firms, that is, firms for which

[30] This method provides the same insights as aggregating the estimated coefficients γ_c^n from Equation (4) using the price impacts $b_{k,n}$ from Equation (2), but is more convenient because it can also be applied for our expanding window betas and easily accommodates the rank-transformation we apply to the exposures (see Section 2.4). Since the estimation error is in the left-hand side exposures $\beta_{i,k,t}$, we obtain consistent estimates of the loadings on characteristics.

the stock return is relatively low upon a surprise increase in the short-rate. This finding is consistent with the idea that these firms face difficulties when interest rates increase because they cannot easily substitute external financing with internal funds, as argued in Gürkaynak, Karasoy-Can, and Lee (2022). Consistent with this finding, the loading on investment is also negative in both panels. Finally, duration is positively associated to exposure to the short rate-news component in both panels, just like it is to the stock market-news components (the last column). For the stock market-news component, profitability and book-to-market are also important determinants of exposure. The negative (positive) loading on profitability implies that the long-short portfolio is long low profitability (high book-to-market) firms. Consistent with an important role for discount rates, Goncalves (2021b) links these exact three characteristics (duration, profitability, and book-to-market) to reinvestment risk and the premium on short-duration equity.[31]

Given these large loadings, one would expect that benchmark models with factors based on firm characteristics can explain part of the return of our hedge portfolios. To test this idea, we present evidence from standard time-series regressions of the monthly returns of the long-short hedge portfolios on the Fama and French (2015) five-factor model in Table VIII. Looking at the in-sample evidence (using characteristic-based exposures) first, we see that many factor exposures are significant and the model explains a large share of the time-series variation in hedge portfolio returns. The R^2 ranges from 0.22 for the long-short portfolio for the term spread-news component to 0.70 for the stock market-news component. Consistent with these large exposures, αs are considerably smaller in the five-factor model than in the CAPM (see Table III). Consider the hedge portfolio for the stock market-news component. Even though it captures a significant α in the five factor model of -3.84%, this α is less than half of what we found in the CAPM (-8.04%). In the out-of-sample test, the five-factor model is even more successful in explaining average returns, as no hedge portfolio generates a significant α. For instance, the five-factor model α for the hedge portfolio for the stock

[31] The fact that the loading on book-to-market is positive is somewhat surprising in this context, because – holding profitability constant – one would expect firms with poor investment opportunities (high book-to-market) to have lower duration and therefore be less exposed to discount rate news.

market-news component drops to an insignificant -2.16%. This result obtains even though factor exposures (and thus R^2) are smaller in the out-of-sample test.[32]

Overall, the evidence in this section is consistent with the idea that characteristics in general, and the characteristics that form the basis of the five-factor model in particular, capture variation in expected returns because they are correlated to exposures to MA surprises that investors care about. The flipside of this idea is that benchmark factors are able to capture a substantial part of the returns of our hedge portfolios. Interestingly, the long-short portfolio for the stock market-news component loads significantly only on one factor in the out-of-sample test, that is, the profitability factor. Consistent with the evidence from Table VII, this loading is negative, suggesting again that low profitability is a key driver of exposure to MA surprises that impact the stock market through discount rate news.

4.3 One-day price impact

Following the literature on the impact of MAs on bond prices, we now turn to price impacts estimated over a shorter one-day window around the MA (see Equations 2 and 3). We report these alternative price impacts in Table OA.2 and present risk premia that use these one-day price impacts to aggregate MAs in Table OA.4. First and foremost, we see in Table OA.2 that the correlation between one-day and three-day price impacts across MA types is large at around 0.80 for three out of four news components (the only exception is the credit spread, where the correlation is 0.58). Perhaps unsurprisingly given this large correlation, we see in Table OA.4 that these alternative price impacts yield estimates of risk premia that are qualitatively, and in most cases also quantitatively, consistent with what we found before. For instance, the risk premium for exposure to the stock market-news component is negative both in- and out-of-sample, whereas the risk premium for exposure to the short rate-news component is positive in the in-sample test but negative in the out-of-sample test.

[32]This finding is perhaps unsurprising, because some of the factors are based on the same characteristics that are used to construct the hedge portfolios.

4.4 Conditional price impact

Previous literature argues that price impacts for some MA types vary over the business cycle (see, e.g., McQueen and Roley, 1993; Boyd, Hu, and Jagannathan, 2005)). To understand how such variation impacts our results, we first extend Equations (2) and (3) to estimate the conditional price impact for each MA type using the Chicago Fed National Activity Index (CFNAI-MA3). For instance, to estimate the conditional stock market impact of an announcement of type n on day d of month t, we run:

$$R_{d(t):d(t)+2} = a_n^0 + a_n^1 CFNAI_{t-1} + b_n^0 S_{n,d(t)} + b_n^1 (S_{n,d(t)} CFNAI_{t-1}) + \epsilon_{d(t):d(t)+2}. \tag{13}$$

We report b_n^0, b_n^1 and the R^2 from this regression for all four news components k in Table OA.5.

Focusing on the stock market news component, two results stand out. First, for one-fifth of the MA types there is significant business cycle variation in the price impact. In all these cases (and for a few other MA types as well), the coefficient estimate b_n^1 is so large that the predicted price impact switches sign between recessions and expansions. Take the example of New Home Sales (NHSLTOT). For this MA type, the estimated price impact is roughly zero when CFNAI is at its mean. For a one standard deviation increase in the CFNAI, the price impact changes by -0.52 (= 0.4×-1.308). This change is economically large: 52 bps translates to about 28% of the unconditional standard deviation of three-day cumulative stock market returns. Second, for the typical MA type, the R^2 in the conditional regression is considerably larger than the R^2 from the unconditional regression reported in Table OA.1. For instance, the R^2 for NHSLTOT increases from about zero in the unconditional regression to 0.06 in the conditional regression. For the other three news components, we similarly find that the price impact varies in recessions versus expansions for a substantial number of MA types.

To understand how this business cycle-variation impacts our risk premium estimates for each news component k, we sort stocks on exposures aggregated as follows (in the spirit of

Equation (6)):

$$\beta^X_{i,k,t} = \sum_{n=1}^{N} \beta^X_{i,n,t} b_{n,k,t} \tag{14}$$

where $b_{n,k,t} = b^0_{n,k} + b^1_{n,k} CFNAI_{t-1}$. Thus, the relative weight on a firm's exposure to MA type n varies with the state of the economy. Here we focus on the characteristic-based exposures, $\beta^X_{i,n,t}$, and we also consider a specification whether these exposures are allowed to vary over the business cyle. In this case, we add interactions with the CFNAI to Equation (4). We present the risk premium estimates (CAPM αs of the value-weighted long-short quintile portfolio) in Table OA.6.

In short, our risk premium estimates allowing for business cycle variation in price impacts are quite similar to what we found above. For instance, the risk premium for the stock market news component is negative and significant at about -5.5% (t-stat< -3), independent of whether we allow exposures to vary with the CFNAI. Similarly, the risk premia for the short rate and term spread news components are consistently positive.[33] We conclude that our main conclusions are robust to business-cycle variation in price impacts.

4.5 Other robustness checks

We show in Table OA.7 that our main result – a negative risk premium for exposure to the stock market-news component of MA surprises – is robust in many dimensions. First, we use only the subset of five characteristics of Ozdagli and Velikov (2020) or the four characteristics that make up the Fama and French (2015) model to estimate the characteristic-based exposures (see Equation (4)). Thus, our results are robust to the choice of characteristics. Second, we use the approach of Vasicek (1973) to shrink the MA surprise exposures estimated over an expanding window (see Equation (5)) to zero or to the cross-sectional mean. This finding is consistent with the idea that we already reduce noise substantially by aggregating exposures

[33] Under the null that exposure to a news component is priced and price impact is time-varying, one would expect larger risk premia in this exercise. However, the conditional price impacts are harder to estimate, both for the econometrician and the investor that desires to hedge. Empirically, risk premia tend to be a bit smaller in magnitude in the conditional exercise, which suggests that the latter effect dominates.

across MA types. Third, we present, if anything, stronger results when the long-short hedge portfolio is sorted on exposures that do not explicitly control for market beta (in which case exposures end up being more correlated to market beta). Fourth, we use a larger set of 46 MA types with Bloomberg relevance scores higher than 75 and all announcements in Gilbert, Scotti, Strasser, and Vega (2017). For this larger set of announcements, the results are only slightly weaker than when using the top 25, which is consistent with the idea that we are adding MA types with lower relevance and this may increase the noise in our procedure. Said differently, by studying the top 25 MA types we have already incorporated all the information needed to identify the primitive sources of news in MA surprises that matter to investors. Fifth, we rank-normalize the price impacts ($b_{n,k}$, see Equation (3)) before using them to aggregate exposures to the news component-level. This test alleviates the concern that the most extreme price impacts used in our main aggregation procedure may have been estimated with more error. Sixth, we do not orthogonalize the stock market return from the other three news components when we estimate the price impact regression of Equation (3). Seventh, we do not rank-normalize the exposures $\beta_{i,n,t}$ to the interval $[0, 1]$ (see Section 2.4). Eighth, we estimate the loadings on characteristics in Equation 4 over an expanding window to construct out-of-sample exposures that are a function of firm characteristics.

Conclusion

The asset pricing implications of macroeconomic announcements (MAs) have been the subject of many studies over the past decade. Existing work has largely focused on the high average market returns earned on MA days or singled out one particular announcement type to determine risk premia. Consequently, relatively little is known about the nature of the information bundle revealed to investors on MA days. Does employment or inflation news imply an increase in credit risk, a larger equity premium or a change in the level or shape of the yield curve? And what is the risk premium that investors demand for exposure to surprises that impact these individual news components?

We develop a new methodology that relies on a large set of MA types to answer these questions. Using variation across MA types in price impacts, we disentangle the primitive news components, i.e. news about the short-term rate, term spread, credit spread, and stock market. Aggregating stock's exposures to MA surprises up to the news component-level, we are able to construct hedge portfolios and estimate risk premia for each news component. Overall, we find evidence that news about the short-term rate, term spread, and stock market captures a risk premium and can be hedged ex post.

Compared to existing evidence in the literature, our evidence for the stock market is most surprising: Investors require a 5 to 8% higher market-adjusted return for a (monthly rebalanced) portfolio that pays off around MAs that negatively impact the stock market. Further, investing in this portfolio eliminates over 40% of the stock market price impact of these MAs ex post. Thus, investors can reduce the stock market price impact of MAs on their portfolio while substantially increasing their expected return (and Sharpe ratio).

This finding challenges the common view that stock market declines are associated with states of high marginal utility. A potential explanation lies in our focus on price impacts in short windows around MAs. These impacts are either driven by cash flow or discount rate news. Cash flow news cannot explain our results, because a portfolio that pays off around MAs that negatively impact expected future cash flows is attractive as a hedge. Discount rate news can only explain our results if increasing discount rates are good news, such as in the ICAPM with reinvestment risk of Goncalves (2021a). Intuitively, a portfolio that pays off around MAs that positively impact the discount rate is risky, because it increases exposure to reinvestment risk.

Our results provide critical information for models designed to match the asset pricing implications of MAs, because news of changing discount rates, not news of changing cash flows, seems to matter most to investors. We leave for future work the challenging task of finding the cause of this discount rate variation: is it time-variation in risk aversion (or preferences, more generally) or the quantity of risk (stock- and macro- (co-)variances)? Note that our methodology is general and can be applied to other news components (such as changes in expectations of growth and volatility) or allowing news content to vary over the business cycle. We also leave these interesting directions for future work.

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Table I: **Top 25 Macroeconomic Announcement Types.**
This table presents the 25 MA types with highest Bloomberg relevance (as of November 2021) that we study in this paper. FOMC data is from Bauer, Lakdawala, and Müller (2021). Data for the other macroeconomic series are from Bloomberg. "A" stands for advance, "P" for preliminary, and "F" for final release.

Ticker	Event	Score	Start Date	End Date	Obs
NFP TCH Index	Change in Nonfarm Payrolls	99.21	10/01/1997	07/02/2020	277
INJCJC Index	Initial Jobless Claims	98.43	03/07/1997	20/02/2020	1174
FDTR Index Target	FOMC Target	97.64	08/02/1990	25/06/2008	148
FDTR Index Path	FOMC Path	97.64	08/02/1990	13/06/2018	230
GDP CQOQ Index A	GDP Annualized QoQ A	96.85	30/04/1997	30/01/2020	92
GDP CQOQ Index P	GDP Annualized QoQ P	96.85	28/05/1997	27/11/2019	90
GDP CQOQ Index F	GDP Annualized QoQ F	96.85	26/03/1997	20/12/2019	91
CPI CHNG Index	CPI MoM	96.06	12/12/1996	13/02/2020	283
NAPMPMI Index	ISM Manufacturing	95.28	01/11/1996	03/02/2020	281
CONSSENT Index P	U. of Mich. Sentiment P	94.49	14/05/1999	14/02/2020	249
CONSSENT Index F	U. of Mich. Sentiment F	94.49	28/05/1999	31/01/2020	250
RTSDCHNG Index	Advance Retail Sales	93.70	14/11/1996	14/02/2020	281
CONCCONF Index	Conf. Board Consumer Confidence	92.91	25/02/1997	25/02/2020	277
DGNOCHNG Index	Durable Goods Orders	92.13	26/11/1997	28/01/2020	267
IP CHNG Index	Industrial Production MoM	91.34	15/11/1996	14/02/2020	279
NHSLTOT Index	New Home Sales	90.55	29/08/1997	27/01/2020	269
NHSPSTOT Index	Housing Starts	89.76	17/03/1998	19/02/2020	264
USURTOT Index	Unemployment Rate	89.29	10/01/1997	07/02/2020	276
ADP CHNG Index	ADP Employment Change	88.19	30/08/2006	05/02/2020	163
ETSLTOTL Index	Existing Home Sales	87.40	23/03/2005	21/02/2020	180
PPI CHNG Index	PPI MoM	86.61	12/12/1997	19/02/2020	266
PCE CRCH Index	Personal Spending	85.83	03/02/1997	31/01/2020	276
PITLCHNG Index	Personal Income	85.83	31/10/1996	31/01/2020	280
TMNOCHNG Index	Factory Orders	85.04	01/11/1996	04/02/2020	281
USTBTOT Index	Trade Balance	84.25	19/12/1996	05/02/2020	280

Table II: **Top Announcement Types per News Component**

This table reports the three MA types with the largest positive (left panel) and negative (right panel) impact on the short-term rate (Panel A), term spread (Panel B), credit spread (Panel C) and stock market (Panel D). The price impacts (denoted $b_{k,n}$ in the paper) are estimated over three-day windows (see Eq. (2) and (3)) and we also report the accompanying t-statistic and R^2. The surprises are standardized to have mean equal to zero and variance equal to one. White standard errors are used.

Largest Positive Impact				Largest Negative Impact			
MA Type	Impact	t-stat	R^2	MA Type	Impact	t-stat	R^2
			Panel A: Short-Term Rate				
Change in Nonfarm Payrolls	0.027	6.563	0.131	U. of Mich. Sentiment P	-0.009	-1.058	0.009
ISM Manufacturing	0.023	3.881	0.092	Initial Jobless Claims	-0.008	-3.236	0.011
Advance Retail Sales	0.023	3.882	0.116	Unemployment Rate	-0.007	-0.974	0.006
			Panel B: Term Spread				
FOMC Path	0.017	1.950	0.029	Personal Spending	-0.008	-1.948	0.007
Advance Retail Sales	0.015	2.786	0.029	FOMC Target	-0.006	-0.491	-0.003
U. of Mich. Sentiment P	0.014	1.748	0.016	Initial Jobless Claims	-0.005	-1.902	0.003
			Panel C: Credit Spread				
Factory Orders	0.005	1.628	0.011	Industrial Production MoM	-0.016	-1.239	0.061
ADP Employment Change	0.005	1.112	0.003	U. of Mich. Sentiment P	-0.008	-1.372	0.016
FOMC Target	0.004	1.040	0.004	U. of Mich. Sentiment F	-0.007	-2.545	0.018
			Panel D: Stock Market				
ADP Employment Change	0.460	2.877	0.052	FOMC Path	-0.527	-4.108	0.072
GDP Annualized QoQ P	0.355	1.432	0.013	FOMC Target	-0.344	-1.815	0.028
Personal Spending	0.158	1.234	0.005	Factory Orders	-0.221	-1.542	0.011

Table III: **Risk Premia**

This table reports our estimate of the risk premium for exposure to each news component k (short-rate, term spread, credit spread, and stock market). These risk premia are estimated as the monthly CAPM α (market βs are reported in the last column) of a value-weighted long-short quintile portfolio sorted on exposures to MA surprises aggregated at the news component-level (denoted $\beta_{i,k}$, see Equations 6 and 6). Panel A reports risk premia for the full sample from 1977 to 2019, where exposures are estimated in-sample as a function of eight firm characteristics (with the firm's market beta as a control). Panel B reports our measure of risk premia that focuses only on the period with backdated exposures based on firm characteristics in the pre-announcement sample (from 1977 to 1994). Panel C reports our "out-of-sample" measure of risk premia estimated over the period 2002 to 2019 and based on exposures that are estimated over expanding windows starting the first day an MA type enters our sample. The expanding window regressions run three-day firm returns around MAs on the market and the surprises for each particular MA type.

News Component	Low	2	Mid	4	High	H-L α	H-L β
Panel A: Characteristic-based exposures (Full Sample)							
Short-Rate	-0.05	-0.01	0.15	0.20	0.24	0.29	0.07
	(−1.04)	(−0.15)	(1.72)	(2.08)	(2.14)	(2.31)	(2.41)
Term Spread	-0.22	0.03	0.08	0.10	0.24	0.46	-0.06
	(−2.76)	(0.44)	(1.30)	(1.45)	(2.73)	(4.31)	(−2.72)
Credit Spread	0.09	-0.02	0.00	0.00	0.03	-0.06	0.08
	(2.02)	(−0.33)	(0.01)	(−0.05)	(0.23)	(−0.52)	(2.96)
Stock Market	0.13	0.08	0.13	-0.01	-0.54	-0.67	0.39
	(2.68)	(1.26)	(1.50)	(−0.11)	(−4.46)	(−4.89)	(12.64)
Panel B: Characteristic-based exposures (Pre-MA sample)							
Short-Rate	-0.18	0.00	0.02	0.20	0.26	0.44	-0.02
	(−2.25)	(−0.02)	(0.20)	(1.57)	(1.70)	(2.36)	(−0.51)
Term Spread	-0.28	-0.16	-0.02	0.13	0.33	0.60	-0.18
	(−2.41)	(−1.77)	(−0.20)	(1.41)	(2.58)	(3.52)	(−4.77)
Credit Spread	0.08	-0.13	-0.06	-0.02	-0.09	-0.16	0.15
	(1.02)	(−1.45)	(−0.50)	(−0.16)	(−0.62)	(−1.04)	(4.42)
Stock Market	0.07	0.08	0.00	-0.07	-0.51	-0.57	0.25
	(0.95)	(0.95)	(0.00)	(−0.52)	(−3.12)	(−3.05)	(5.99)
Panel C: Expanding Window Exposures (Out-of-Sample)							
Short-Rate	0.16	0.19	0.18	0.04	-0.04	-0.20	0.18
	(1.75)	(2.16)	(2.44)	(0.51)	(−0.49)	(−1.97)	(7.32)
Term Spread	0.05	0.23	0.20	0.02	0.05	0.00	0.21
	(0.37)	(2.93)	(2.66)	(0.18)	(0.39)	(−0.02)	(4.34)
Credit Spread	-0.01	0.08	0.19	0.13	0.12	0.14	-0.30
	(−0.10)	(0.79)	(2.35)	(1.59)	(1.40)	(0.91)	(−8.44)
Stock Market	0.27	0.15	0.13	0.14	-0.13	-0.40	0.17
	(2.94)	(1.88)	(1.68)	(1.71)	(−0.93)	(−2.46)	(4.34)

TABLE IV: **Ex-post Exposures**

This table reports ex-post exposures (see Eq. (8)) of the news components and the long-short hedge portfolios to MA surprises. These exposures are estimated by regressing three-day changes in yields (for the short-rate, term spread, and credit spread news components) or cumulative returns (for the stock market-news component as well as all hedge portfolios) on MA surprises, where the surprise in each MA type n is weighted by its impact ($b_{n,k}$) on the corresponding news component k. To make the magnitudes of these exposures comparable, each hedge portfolio is rescaled to have the same volatility as the corresponding news component. The in-sample hedge portfolio is constructed by sorting on an exposure aggregated at the news component-level: $\beta_{i,k,t} = \Sigma_n b_{n,k} \times \beta_{i,n,t}$, where $\beta_{i,n,t}$ is a function of one-month lagged firm characteristics and this function is estimated over the full sample. The out-of-sample hedge portfolio is constructed by sorting on $\beta_{i,k,t} = \Sigma_n b_{n,k,t} \times \beta_{i,n,t}$, where $\beta_{i,n}$ and $b_{n,k,t}$ are estimated over an expanding window. We control for announcement type fixed effects and cluster standard errors monthly.

		Short-Rate	Term Spread	Credit Spread	Stock Market
News Component	Exposure	1.000	1.000	1.000	1.000
	t-stat	(8.761)	(6.405)	(2.131)	(6.376)
	R^2	0.024	0.010	0.009	0.007
Hedge Portfolio (In-Sample)	Exposure	0.218	0.267	0.152	0.517
	t-stat	(2.466)	(2.125)	(0.968)	(3.423)
	R^2	0.001	0.001	0.000	0.002
Hedge Portfolio (Out-of-sample)	Exposure	0.245	0.247	-0.062	0.413
	t-stat	(2.803)	(1.482)	(−0.356)	(1.997)
	R^2	0.002	0.001	0.000	0.001

Table V: **Ex-post Exposures to the Top Announcements**
This table reports ex-post exposures of the in- and out-of-sample hedge portfolios (see Table IV) to the surprises in the MA types with the largest positive and negative price impacts on the corresponding news component (short-term rate, term spread, credit spread, and stock market). We focus on the top and bottom one, two and three MA types. These exposures are estimated following Eq. (8). We control for announcement type fixed effects and cluster standard errors monthly.

	Short-Rate	Term Spread	Credit Spread	Stock Market
	Panel A: Hedge Portfolio (In-Sample)			
Top & Bottom 1	0.389	0.281	0.421	0.540
	(2.334)	(0.824)	(1.843)	(3.048)
Top & Bottom 2	0.260	0.232	0.440	0.570
	(2.219)	(1.095)	(2.095)	(3.172)
Top & Bottom 3	0.228	0.103	0.388	0.558
	(2.116)	(0.533)	(2.055)	(3.539)
	Panel B: Hedge Portfolio (Out-of-Sample)			
Top & Bottom 1	0.501	-0.557	-0.058	0.765
	(2.264)	(−1.104)	(−0.221)	(2.631)
Top & Bottom 2	0.377	-0.376	-0.118	0.528
	(2.817)	(−1.126)	(−0.556)	(2.116)
Top & Bottom 3	0.299	-0.393	-0.157	0.389
	(2.711)	(−1.431)	(−0.826)	(1.736)

Table VI: **Risk Premia for Portfolios that Hedge Cash Flow News**
This table reports our estimate of the risk premium for exposure to MA surprises that impact the expected dividend growth series of Pettenuzzo, Sabbatucci, and Timmermann (2020). This risk premium is estimated as the monthly CAPM α of a value-weighted long-short quintile portfolio sorted on exposures to MA surprises aggregated across MA types n using the price impact of each MA type on the expected cash flow series. Panel A reports risk premia for the full sample from 1977 to 2019, where exposures are estimated in-sample as a function of eight firm characteristics (with the firm's market beta as a control). Panel B reports our measure of risk premia that focuses only on the period with backdated exposures based on firm characteristics in the pre-announcement sample (from 1977 to 1994). Panel C reports our "out-of-sample" measure of risk premia estimated over the period 2002 to 2019 and based on exposures that are estimated over expanding windows starting the first day an MA type enters our sample. The expanding window regressions run three-day firm returns around MAs on the market and the surprises for each particular MA type. t-statistics in parentheses.

	Risk Premium
Characteristic-Based Exposures (Full Sample)	-0.153
	(−0.965)
Characteristic-Based Exposures (Pre-MA Sample)	0.155
	(0.644)
Expanding Window Exposures (Out-of-Sample)	-0.148
	(−1.025)

Table VII: **Aggregated Exposures on Firm Characteristics**
This table reports results from the pooled regressions of the rank-transformed exposures $\beta_{i,k,t}$ (for each news component) on eight firm characteristics: Whited and Wu (2006) financial constraints index, cash, duration, volatility, profitability, size, book-to-market value, and investment. We run these regressions both for the in-sample exposures estimated as a function of firm characteristics (Panel A) as well as for out-of-sample exposures estimated over an expanding window (Panel B). These regressions control for firm and industry fixed effects. The loadings are directly comparable across characteristics for each news component, because the firm characteristics are standardized. In Panel B, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, using firm and date clustered standard errors. There is no need to test significance in Panel A, because the exposures are a linear combination of these characteristics by construction. All coefficients are rescaled by 100.

	Short-Rate	Term Spread	Credit Spread	Stock Market
Panel A: Characteristic-Based Exposures (Full Sample)				
Whited-Wu	−1.1565	0.4458	0.4458	1.5926
Cash	0.4741	0.4742	0.4742	−4.8460
Duration	0.2078	−0.2515	−0.2515	3.6196
Volatility	−0.0890	−0.0852	−0.0852	−0.9329
Profitability	0.2777	0.5067	0.5067	−15.7495
Size	−1.2170	0.1887	0.1887	−13.0908
Book-to-Market	−0.0639	0.1343	0.1343	4.6541
Investment	−0.3625	−0.2259	−0.2259	12.6693
Panel B: Expanding Window Exposures (Out-of-Sample)				
Whited-Wu	−0.0906**	0.0542*	−0.1975***	−0.1865
Cash	−0.0621**	0.0326	−0.0544**	−0.3971
Duration	0.0487**	−0.0012	0.0035	0.9271***
Volatility	−0.0571	0.0257	−0.0752**	0.3577
Profitability	−0.0580*	0.1206***	−0.1275***	−0.7652**
Size	0.3093***	−0.2290***	0.4761***	0.3840
Book-to-Market	−0.0302	0.0885***	−0.0553**	1.0436***
Investment	−0.0110	−0.0376***	0.0056	−0.0627

Table VIII: **Can the Fama and French (2015) Explain the Returns of Our Hedge Portfolios?**

This table reports coefficient estimates and the R^2 from standard monthly time-series regressions of the hedge portfolios on the Fama and French (2015) five-factor model. We run these regressions for the hedge portfolios constructed using in-sample exposures estimated as a function of firm characteristics (Panel A) as well as for the hedge portfolios constructed using out-of-sample exposures estimated over an expanding window (Panel B). The sample period in Panel A (Panel B) is from 1977 to 2019 (2002 to 2019).

News Component	α^{FF5}	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	R^2
Panel A: Characteristic-Based Exposures (1977 to 2019)							
Short-Rate	-0.08	0.13	0.57	0.48	0.22	0.15	0.56
	(−0.88)	(5.85)	(17.80)	(11.59)	(5.39)	(2.37)	
Term Spread	0.39	-0.04	0.12	0.27	-0.21	0.16	0.22
	(3.96)	(−1.67)	(3.40)	(5.89)	(−4.63)	(2.23)	
Credit Spread	-0.44	0.12	0.59	0.26	0.51	0.00	0.47
	(−4.76)	(5.18)	(17.63)	(6.16)	(12.09)	(0.06)	
Stock Market	-0.32	0.13	0.57	0.04	-0.39	-0.66	0.70
	(−3.52)	(6.08)	(17.53)	(0.85)	(−9.48)	(−10.18)	
Panel B: Expanding Window Exposures (2002 to 2019)							
Short-Rate	-0.14	0.15	-0.02	-0.09	-0.17	0.02	0.24
	(−1.30)	(5.33)	(−0.55)	(−1.92)	(−2.89)	(0.22)	
Term Spread	0.07	0.09	0.23	-0.04	-0.30	0.24	0.17
	(0.36)	(1.66)	(2.66)	(−0.49)	(−2.77)	(1.75)	
Credit Spread	0.13	-0.23	-0.27	0.05	0.09	-0.05	0.32
	(0.87)	(−5.56)	(−4.10)	(0.71)	(1.06)	(−0.52)	
Stock Market	-0.18	0.04	0.06	0.04	-0.47	-0.16	0.20
	(−1.15)	(0.83)	(0.85)	(0.60)	(−5.37)	(−1.42)	

Online Appendix to "Macroeconomic Announcements and the News that Matters Most to Investors"

Table OA.1: Risk Premia and Price Impacts for All MA Types

This table reports for all 25 MA types the risk premia and price impacts on each of the four news components. Risk premia are estimated as the monthly CAPM α of the high-minus-low portfolio from sorting stocks on exposure to each MA type n, which exposure is estimated as a function of lagged firm characteristics (see Eq. (4)). The returns of these portfolios cover the sample period from 1977 to 2019. The price impact for each MA type n on each news component k (denoted $b_{n,k}$ in the paper) is estimated by regressing three-day cumulative changes in the short-term rate, term spread, and credit spread or three-day stock market returns on surprises (S_n, standardized to have mean equal to zero and variance equal to one) over the sample for which the MA is available (starting in the mid-1990s or later until 2019).

	Risk Premia		Short-Rate			Term Spread			Credit Spread			Stock Market		
Ticker	α^{CAPM}	t-stat	Impact	t-stat	R^2	Impact	t-stat	R^2	Impact	t-stat	R^2	Impact	t-stat	R^2
NFP TCH Index	0.330	2.921	0.027	6.563	0.131	0.010	1.746	0.010	-0.001	-0.474	-0.003	-0.002	-0.017	-0.004
INJCJC Index	0.260	1.942	-0.008	-3.236	0.011	-0.005	-1.902	0.003	0.003	1.987	0.003	0.006	0.108	-0.001
FDTR Index Target	-0.043	-0.262	0.020	1.839	0.038	-0.006	-0.491	-0.003	0.004	1.040	0.004	-0.344	-1.815	0.028
FDTR Index Path	0.199	1.164	0.021	3.496	0.072	0.017	1.950	0.029	0.004	0.850	0.000	-0.527	-4.108	0.072
GDP CQOQ Index A	-0.095	-0.507	0.013	1.340	0.021	0.006	0.690	-0.006	0.004	0.568	-0.006	0.061	0.299	-0.011
GDP CQOQ Index P	-0.209	-1.315	0.004	0.671	-0.008	0.009	1.438	0.004	-0.006	-1.421	0.007	0.355	1.432	0.013
GDP CQOQ Index F	0.196	1.109	0.000	0.055	-0.012	-0.001	-0.174	-0.012	0.001	0.242	-0.011	-0.087	-0.565	-0.010
CPI CHNG Index	0.183	1.132	0.003	0.713	-0.002	0.007	0.961	0.002	0.001	0.303	-0.003	-0.126	-0.936	0.001
NAPMPMI Index	0.050	0.453	0.023	3.881	0.092	0.010	1.812	0.011	-0.004	-1.163	0.007	0.111	0.771	0.000
CONSSENT Index P	0.461	3.648	-0.009	-1.058	0.009	0.014	1.748	0.016	-0.008	-1.372	0.016	-0.155	-1.410	0.004
CONSSENT Index F	-0.212	-1.556	0.001	0.270	-0.004	-0.001	-0.225	-0.004	-0.007	-2.545	0.018	0.048	0.495	-0.004
RTSDCHNG Index	0.279	1.975	0.023	3.882	0.116	0.015	2.786	0.029	-0.004	-0.957	0.001	-0.136	-1.098	0.002
CONCCONF Index	0.139	0.884	0.011	2.405	0.019	0.008	1.108	0.006	0.001	0.153	-0.004	-0.019	-0.111	-0.004
DGNOCHNG Index	-0.199	-1.112	0.004	0.785	0.000	0.008	1.549	0.008	0.000	0.010	-0.004	0.041	0.355	-0.003
IP CHNG Index	-0.139	-1.023	-0.001	-0.044	-0.004	0.000	0.012	-0.004	-0.016	-1.239	0.061	-0.150	-0.600	0.002
NHSLTOT Index	0.034	0.180	0.007	1.619	0.006	0.008	1.936	0.008	0.000	0.014	-0.004	-0.053	-0.535	-0.003
NHSPSTOT Index	0.206	1.251	0.001	0.233	-0.004	-0.001	-0.219	-0.004	-0.002	-0.474	-0.003	-0.029	-0.261	-0.004
USURTOT Index	0.234	1.725	-0.007	-0.974	0.006	0.011	1.626	0.012	0.001	0.407	-0.003	0.002	0.017	-0.004
ADP CHNG Index	-0.592	-3.927	0.006	1.102	0.000	0.007	1.201	0.001	0.005	1.112	0.003	0.460	2.877	0.052
ETSLTOTL Index	0.376	2.964	0.002	0.808	-0.004	0.008	1.350	0.006	-0.003	-0.775	-0.004	0.108	0.678	-0.003
PPI CHNG Index	0.079	0.451	0.001	0.238	-0.004	0.002	0.267	-0.004	-0.003	-0.884	-0.002	-0.078	-0.562	-0.002
PCE CRCH Index	0.025	0.170	0.011	2.380	0.030	-0.008	-1.948	0.007	0.002	1.073	0.000	0.158	1.234	0.005
PITLCHNG Index	-0.001	-0.006	0.003	1.008	-0.002	0.000	0.075	-0.004	0.002	0.630	-0.002	-0.038	-0.444	-0.003
TMNOCHNG Index	0.086	0.488	0.001	0.264	-0.003	0.000	0.091	-0.004	0.005	1.628	0.011	-0.221	-1.542	0.011
USTBTOT Index	-0.291	-2.183	-0.003	-0.596	-0.002	0.011	1.805	0.013	-0.002	-0.924	-0.001	0.071	0.602	-0.002

Table OA.2: **One-Day Price Impacts**

This table presents price impacts similar to Table OA.1, but now uses a one-day window around the MA. Thus, price impacts are estimated – for each MA type n – by regressing the change in the short-term rate, term spread, and credit spread or the stock market return on the day of the MA on the surprises (S_n, standardized to have mean equal to zero and variance equal to one). In the last row of the table, we report the correlation with three-day price impacts.

	Short-Rate			Term Spread			Credit Spread			Stock Market		
Ticker	Impact	t-stat	R^2	Impact	t-stat	R^2	Impact	t-stat	R^2	Impact	t-stat	R^2
NFP TCH Index	0.025	7.611	0.236	0.013	3.260	0.050	0.001	0.449	-0.003	-0.144	-1.833	0.011
INJCJC Index	-0.008	-4.971	0.035	-0.004	-2.824	0.006	0.001	1.636	0.002	0.010	0.272	-0.001
FDTR Index Target	0.027	4.618	0.218	-0.020	-4.339	0.274	-0.003	-1.452	0.014	-0.241	-1.868	0.043
FDTR Index Path	0.023	6.514	0.243	0.012	2.831	0.032	-0.004	-1.992	0.015	-0.456	-3.736	0.130
GDP CQOQ Index A	0.010	1.866	0.048	0.003	0.618	-0.009	0.002	0.712	-0.004	-0.088	-0.668	-0.006
GDP CQOQ Index P	0.000	-0.074	-0.012	0.002	0.387	-0.010	-0.003	-1.221	0.000	0.009	0.071	-0.012
GDP CQOQ Index F	0.003	0.814	-0.002	-0.003	-0.523	-0.006	0.003	1.051	0.000	-0.022	-0.261	-0.011
CPI CHNG Index	0.005	1.862	0.010	0.002	0.443	-0.003	0.000	0.010	-0.004	-0.139	-1.147	0.008
NAPMPMI Index	0.016	5.689	0.128	0.013	3.855	0.054	0.000	-0.173	-0.004	0.033	0.428	-0.003
CONSSENT Index P	0.006	1.304	0.012	0.005	1.450	0.006	-0.005	-1.502	0.018	-0.123	-1.705	0.009
CONSSENT Index F	0.000	0.006	-0.004	0.004	1.253	0.001	-0.003	-1.861	0.010	-0.109	-1.684	0.006
RTSDCHNG Index	0.010	4.782	0.081	0.012	4.587	0.053	-0.002	-1.274	0.002	0.047	0.605	-0.002
CONCCONF Index	0.007	3.040	0.031	0.005	1.437	0.007	0.002	1.094	0.000	-0.089	-0.718	0.002
DGNOCHNG Index	0.003	0.619	0.001	0.003	1.096	0.001	-0.001	-0.580	-0.003	0.045	0.644	-0.002
IP CHNG Index	0.005	0.861	0.005	0.004	0.845	0.003	-0.004	-1.138	0.021	-0.094	-0.848	0.003
NHSLTOT Index	0.003	1.033	0.001	0.006	2.525	0.013	0.000	-0.127	-0.004	-0.057	-0.939	-0.001
NHSPSTOT Index	0.001	0.320	-0.004	0.001	0.492	-0.003	-0.002	-1.002	-0.001	0.006	0.080	-0.004
USURTOT Index	-0.006	-1.879	0.008	0.004	1.015	0.000	0.003	1.826	0.012	0.029	0.402	-0.003
ADP CHNG Index	0.003	1.373	0.008	0.012	3.247	0.066	0.005	2.036	0.033	0.217	1.958	0.038
ETSLTOTL Index	0.002	0.886	-0.003	0.008	1.926	0.020	-0.001	-0.656	-0.003	0.082	0.830	-0.002
PPI CHNG Index	0.001	0.501	-0.002	0.004	1.341	0.006	0.001	0.857	-0.001	-0.068	-1.034	-0.001
PCE CRCH Index	0.004	1.633	0.008	-0.002	-0.634	-0.002	0.003	2.144	0.011	0.054	0.659	-0.001
PITLCHNG Index	-0.001	-0.463	-0.003	0.000	0.066	-0.004	0.001	0.725	-0.002	0.021	0.341	-0.003
TMNOCHNG Index	0.001	0.483	-0.003	0.002	0.618	-0.001	0.000	0.098	-0.004	-0.214	-2.716	0.037
USTBTOT Index	-0.001	-0.458	-0.003	0.006	2.093	0.014	0.001	0.360	-0.004	0.115	1.407	0.006
Corr. with 3-day price impact	0.85			0.74			0.58			0.82		

Table OA.3: **Impacts on Expected Dividend Growth**

This table reports the three-day impact of the surprise in each of 25 MA types on the persistent component of the dividend growth process as extracted in Pettenuzzo, Sabbatucci, and Timmermann (2020).

Ticker	Impact	t-stat	R^2
NFP TCH Index	-0.007	-2.338	0.015
INJCJC Index	0.001	0.632	-0.001
FDTR Index Target	0.005	1.116	0.002
FDTR Index Path	-0.004	-0.931	0.000
GDP CQOQ Index A	0.002	0.350	-0.011
GDP CQOQ Index P	0.002	0.395	-0.011
GDP CQOQ Index F	-0.006	-0.838	0.000
CPI CHNG Index	0.000	-0.046	-0.004
NAPMPMI Index	0.007	2.022	0.014
CONSSENT Index P	-0.001	-0.152	-0.005
CONSSENT Index F	0.006	1.738	0.007
RTSDCHNG Index	0.007	1.872	0.014
CONCCONF Index	0.006	1.769	0.010
DGNOCHNG Index	-0.005	-1.902	0.007
IP CHNG Index	0.004	0.797	0.000
NHSLTOT Index	0.003	1.051	0.000
NHSPSTOT Index	0.005	1.577	0.005
USURTOT Index	-0.008	-1.893	0.017
ADP CHNG Index	-0.001	-0.118	-0.008
ETSLTOTL Index	0.000	-0.075	-0.007
PPI CHNG Index	0.004	1.162	0.001
PCE CRCH Index	-0.003	-0.881	-0.002
PITLCHNG Index	-0.007	-2.352	0.014
TMNOCHNG Index	0.003	0.859	0.000
USTBTOT Index	-0.001	-0.223	-0.004

Table OA.4: **Risk Premia using One-Day Price Impacts**
This table is similar to Table III of the paper with the only difference that we use the one-day price impacts (see Table OA.2) to aggregate exposures. Risk premia are estimated as the monthly CAPM α of a value-weighted long-short quintile portfolio sorted on exposures to MA surprises aggregated at the news component-level (denoted $\beta_{i,k}$, see Equations 6 and 6). We first report risk premia for the full sample from 1977 to 2019, where exposures are estimated in-sample as a function of eight firm characteristics. Next, we report risk premia for the pre-MA sample that focuses only on the period with backdated exposures based on firm characteristics (from 1977 to 1994). Finally, we report our "out-of-sample" measure of risk premia estimated over the period 2002 to 2019 and based on exposures that are estimated over expanding windows starting the first day an MA type enters our sample.

	Short-Rate	Term Spread	Credit Spread	Stock Market
Characteristic-Based (Full Sample)	0.33	0.30	-0.32	-0.72
	(2.83)	(2.29)	(−2.89)	(−5.18)
Characteristic-Based (Pre-MA Sample)	0.50	0.32	-0.40	-0.66
	(2.77)	(1.62)	(−2.42)	(−3.64)
Expanding Window (Out-of-Sample)	-0.18	-0.06	0.18	-0.18
	(−1.61)	(−0.42)	(1.32)	(−1.51)

Table OA.5: **Conditional Price Impacts**

This table reports results for the regression that estimates conditional price impacts (Equation (13)). We report the coefficient estimate for the surprise, b_n^0, as well as the coefficient estimate for the surprise interacted with the CFNAI, b_n^1.

	Short-Rate					Term Spread					Credit Spread					Stock Market				
Ticker	b_n^0	t-stat	b_n^1	t-stat	R^2	b_n^0	t-stat	b_n^1	t-stat	R^2	b_n^0	t-stat	b_n^1	t-stat	R^2	b_n^0	t-stat	b_n^1	t-stat	R^2
NFP TCH Index	0.025	6.568	-0.019	-2.291	0.155	0.014	2.839	0.038	2.877	0.072	-0.001	-0.533	0.004	0.379	-0.001	-0.020	-0.185	0.171	0.415	0.030
INJCJC Index	-0.008	-3.084	0.002	0.418	0.016	-0.006	-2.406	0.000	-0.057	0.014	0.001	0.850	-0.006	-1.381	0.007	0.055	0.976	0.137	0.901	0.005
FDTR Index Target	0.019	1.888	-0.039	-1.296	0.069	-0.006	-0.484	0.003	0.132	-0.019	0.004	1.274	-0.025	-2.885	0.117	-0.347	-1.798	0.559	1.053	0.024
FDTR Index Path	0.020	2.843	0.011	1.804	0.089	0.013	2.311	-0.039	-2.859	0.089	0.001	0.209	-0.012	-1.300	0.018	-0.515	-3.949	-0.057	-0.236	0.064
GDP CQOQ Index A	0.013	1.304	-0.001	-0.114	0.056	0.008	1.099	0.019	3.450	0.079	0.004	0.910	-0.007	-1.488	0.302	0.085	0.392	0.206	0.979	-0.010
GDP CQOQ Index P	0.003	0.452	0.005	1.101	0.005	0.010	1.393	0.017	1.367	0.077	-0.005	-1.489	0.003	0.306	-0.012	0.138	0.839	-0.858	-2.221	0.060
GDP CQOQ Index F	0.000	-0.026	-0.032	-1.814	0.055	0.001	0.172	0.066	3.402	0.107	0.001	0.266	0.009	0.508	-0.016	-0.089	-0.629	0.022	0.029	-0.033
CPI CHNG Index	0.004	0.939	0.003	0.408	-0.008	-0.001	-0.137	-0.033	-1.758	0.038	-0.001	-0.667	-0.011	-1.034	0.008	-0.086	-0.656	0.162	0.702	0.008
NAPMPMI Index	0.019	4.331	-0.020	-1.428	0.132	0.012	2.269	0.012	1.366	0.016	-0.002	-0.696	0.016	1.297	0.054	0.074	0.523	-0.212	-0.814	-0.003
CONSSENT Index P	-0.002	-0.366	0.036	1.369	0.055	0.006	1.082	-0.039	-1.137	0.045	-0.002	-0.523	0.041	1.465	0.145	-0.139	-1.361	0.007	0.015	0.014
CONSSENT Index F	-0.001	-0.442	-0.027	-3.561	0.070	-0.003	-0.561	-0.017	-1.189	0.000	-0.004	-1.574	0.015	2.314	0.074	-0.002	-0.024	-0.499	-2.609	0.015
RTSDCHNG Index	0.022	3.787	-0.001	-0.129	0.114	0.020	3.648	0.011	1.447	0.031	-0.010	-3.384	-0.013	-1.538	0.055	-0.204	-1.461	-0.145	-0.606	0.005
CONCCONF Index	0.010	2.179	-0.003	-0.368	0.016	0.017	3.527	0.025	1.441	0.095	0.000	0.147	0.005	0.449	0.037	0.113	0.896	0.354	0.901	0.030
DGNOCHNG Index	0.004	0.808	-0.009	-0.976	0.061	0.006	1.180	-0.018	-1.543	0.021	0.001	0.524	0.009	1.015	0.035	-0.085	-0.714	-1.154	-3.199	0.101
IP CHNG Index	0.012	2.517	0.040	2.356	0.115	-0.004	-0.858	-0.013	-0.433	-0.002	-0.003	-0.892	0.032	1.503	0.195	0.059	0.507	0.575	1.468	0.039
NHSLTOT Index	0.007	1.569	-0.012	-0.597	0.025	0.009	2.052	-0.008	-0.518	0.005	0.000	-0.133	0.006	0.359	0.003	-0.002	-0.015	-1.308	-3.352	0.061
NHSPSTOT Index	0.002	0.376	0.016	1.228	-0.003	-0.002	-0.407	0.000	-0.010	0.003	-0.002	-0.611	-0.009	-0.466	-0.001	-0.041	-0.409	-0.326	-0.620	-0.006
USURTOT Index	-0.009	-1.653	-0.027	-1.688	0.044	0.011	1.924	0.016	1.010	0.024	0.003	0.819	0.004	0.357	0.000	0.087	0.717	0.107	0.222	0.028
ADP CHNG Index	0.006	1.103	0.006	0.579	0.026	0.008	1.243	-0.002	-0.292	0.012	0.003	0.566	-0.001	-0.137	0.028	0.381	2.732	-0.135	-0.591	0.044
ETSLTOTL Index	0.002	0.653	-0.002	-0.503	-0.010	0.008	1.431	-0.002	-0.131	0.032	-0.001	-0.472	0.006	0.748	-0.004	-0.052	-0.326	-0.773	-2.481	0.090
PPI CHNG Index	-0.003	-0.571	-0.015	-1.557	0.023	-0.007	-1.273	-0.037	-1.912	0.040	-0.002	-0.931	-0.002	-0.182	0.044	-0.092	-0.791	0.015	0.035	0.003
PCE CRCH Index	0.010	2.281	-0.013	-1.224	0.047	-0.008	-1.874	-0.003	-0.332	0.000	0.002	1.006	-0.007	-0.623	0.028	0.212	1.948	0.453	1.331	0.010
PITLCHNG Index	0.002	0.761	-0.006	-1.134	0.014	0.003	0.740	0.009	1.298	-0.007	0.000	0.184	-0.008	-1.095	0.041	-0.013	-0.128	0.051	0.281	-0.009
TMNOCHNG Index	-0.003	-0.709	-0.009	-1.011	0.026	0.001	0.124	-0.004	-0.360	0.043	0.002	0.643	-0.009	-1.878	0.058	-0.302	-2.718	-0.154	-0.653	0.038
USTBTOT Index	-0.002	-0.357	-0.002	-0.349	0.011	0.011	1.878	0.006	0.598	0.015	0.000	0.081	0.019	5.600	0.134	0.063	0.517	-0.147	-0.715	0.001

Table OA.6: **Risk Premia using Conditional Price Impacts**
This table is similar to Table III of the paper with the only difference that we use conditional price impacts to aggregate exposures at the news-component level: $\beta^X_{i,k,t} = \sum_{n=1}^{N} \beta^X_{i,n,t} b_{n,k,t}$. Here, $b_{n,k,t}$ is the conditional price impact of MA type n on news component k and $\beta^X_{i,n,t}$ is the conditional exposure of firm i to MA type n. We consider two alternative definitions for this conditional exposure. First, exposures vary over time only with the firm characteristics X, as in Equation (4). Second, we expand this equation with interactions between the CFNAI and the firm characteristics, to allow for additional business-cycle variation in the relation between the firm characteristics and exposures. Risk premia are estimated as the monthly CAPM α of a value-weighted long-short quintile portfolio sorted on these aggregated exposures $\beta^X_{i,k,t}$.

Short-Rate	Term Spread	Credit Spread	Stock Market
Panel A: Characteristics-based exposures			
0.26	0.11	-0.02	-0.47
(1.98)	(0.82)	(−0.18)	(−3.09)
Panel B: Characteristic-based exposures conditional on CFNAI			
0.10	0.17	-0.27	-0.45
(0.73)	(1.23)	(−1.81)	(−3.18)

Table OA.7: **Additional Robustness Checks**

This table reports results from the robustness checks discussed in Section 4.5 of the paper. For brevity, we focus on the risk premium (CAPM α) for the long-short quintile portfolio based on exposure to the stock market-news component. Specification 1a and 1b vary the set of firm characteristics used to construct exposures (see Eq. (4)), either using only the characteristics from Ozdagli and Velikov (2020) or those from Fama and French (2015). As in the paper, these tests also control for market beta. Specification 2a and 2b shrink the expanding window exposures (see Eq. (5)) using the approach of Vasicek (1973), where we shrink either to the cross-sectional mean or zero (which null is relevant because we control for market beta). In specification 3, we construct the long-short portfolio by sorting stocks on exposures that do not explicitly control for market beta (such that exposures end up being more correlated to market beta). In the characteristics-based specification, this approach amounts to estimating a firm's exposure as a function of the full set of nine characteristics (whereas we subtract out the effect of market beta in our main tests). In the expanding window specification, exposure to each MA type is now estimated using a one-factor model, where the surprise is the only factor. In specification 4, we aggregate (see Eqs. (6) and (7)) over a larger set of 46 MA types with relevance scores higher than 75 and all announcements in Gilbert, Scotti, Strasser, and Vega (2017). In specification 5, we aggregate (see Eqs. (6) and (7)) using three-day price impacts that are rank-normalized across MA types (such that the average weight equals 0 and positive weights sum to 1 and negative weights sum to -1). In specification 6, we do not orthogonalize the daily stock market return from changes in the short-rate, term spread, and credit spread before estimating the price impact using Eq. (3). In specification 7, we do not rank-normalize firm's exposures to each MA type n to the interval $[0, 1]$ (see Eq. (7)). In specification 8, we construct the long-short portfolio by sorting stocks on exposures that are a function of the eight firm characteristics where the loadings (γ_c^n in Equation 4) are estimated in an expanding window.

		Characteristic-Based Exposures (Full Sample)		Expanding Window Exposures (Out-of-Sample)	
Alternative Specification		Risk Premium	t-stat	Risk Premium	t-stat
1a	OV Characteristics	-0.533	-3.191		
1b	FF Characteristics	-0.580	-4.309		
2a	Shrink to Mean			-0.401	-2.366
2b	Shrink to 0			-0.386	-2.276
3	Not controlling for β_{MKT}	-0.541	-2.666	-0.623	-3.015
4	46 MA types	-0.507	-3.396	-0.217	-1.380
5	Rank-normalizing $b_{n,k}$	-0.432	-2.633	-0.390	-2.288
6	Not orthogonalizing $R_{MKT,d:d+2}$	-0.618	-4.508	-0.329	-2.082
7	Not normalizing $\beta_{i,n,t}$	-0.676	-4.590	-0.403	-2.568
8	EW with Characteristics			-0.360	-1.660