# Essays on Macroeconomic Announcements and Asset Pricing

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A dissertation
submitted in partial fulfillment of the
degree of

Doctor of Philosophy

University of Washington
2021

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Program Authorized to Offer Degree:
Foster School of Business

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## Abstract

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The first chapter of my thesis explores the correlation of asset pricing factor sensitivities between firms with important economic links. I find that firms' factor sensitivities (betas) are significantly correlated with their customers' respective betas. I further document this effect holds in the setting of firms in strategic alliances.

The second chapter of my thesis is co-authored with Thomas Gilbert and Christopher Hrdlicka. It highlights a puzzle that one can earn more than 100% of the equity premium by trading on select macroeconomic announcement days identified by prior literature. We use day-of-the-month fixed effects to control for announcement clustering and find that macroeconomic announcements *as a whole* are responsible for about half of the equity premium.

The third chapter of my thesis investigates the role of competition in the risk imposed on firms by organization capital. I find that firms in a spread portfolio of high-minus-low organization capital are significantly riskier only in the most competitive industries.

## ACKNOWLEDGMENTS

I am extremely grateful to the members of my supervisory committee for their guidance and support throughout my academic program: Christopher Hrdlicka, Mark Westerfield, Lukas Kremens, Yu-chin Chen, and especially Thomas Gilbert (chair). I sincerely appreciate their commitment to my academic success, and my work benefited greatly from their advice, insights, and support throughout my time in the Ph.D. program.

I am also thankful for the support from the Finance faculty and my fellow Ph.D. students at the University of Washington. In particular, I thank my dear friends and colleagues: Quentin DuPont and David Shin. Your unwavering support was critical to my academic progress, and I have the utmost respect and appreciation for you.

Finally, thank you to my family for your love, understanding, and support over the years. I especially thank my wife, Carly McClintock, for always being with me during the cycle of achievements and hardships; you are the true wonder of my universe.

## DEDICATION

*To Mom. "Family first; education second." Everything that I have and will ever achieve is because of you. I know that you would be proud of me today. I miss you, Mom.*

# Chapter 1

# Network Effects in Asset Pricing Factor Sensitivities

## 1.1 Introduction

There is a growing literature on the role of economic links in value creation, return predicatability, and risk sharing. McConnell and Nantell (1985) find evidence of wealth gains from joint ventures. Chan et al. (1997) find that there is a positive stock price response across strategic alliances and value creation for partnering firms. Muslu et al. (2013) find evidence of return correlation for stocks who are covered by a shared analyst. Cohen and Frazzini (2008) find evidence of return predictability across economically linked firms due to investor inattention, where the economic link is between firms and customers. Similarly, Cao and Lin (2016) find evidence of return predictability due to investor inattention across strategically aligned firms, where the strategic alliance is "an agreement between two or more parties to pursue a set of agreed-upon objectives while remaining independent organizations."

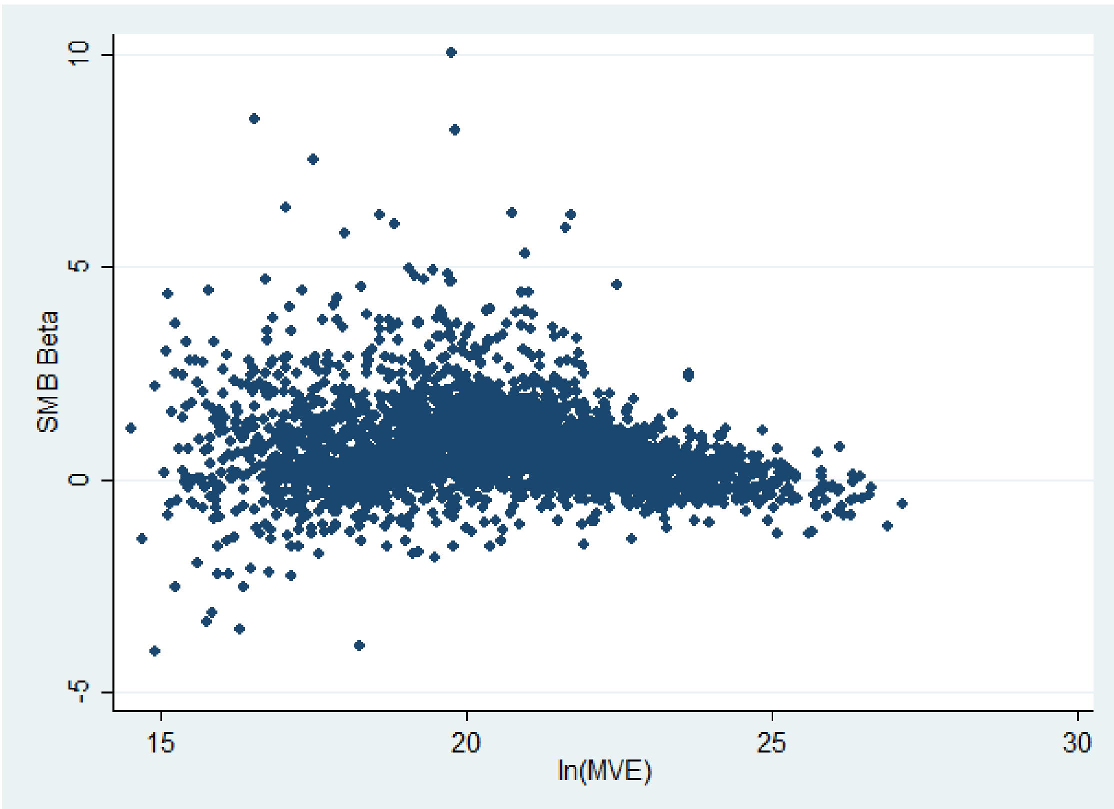
In this paper I investigate the variation in asset pricing factor senstitivites, and the role of economic links as a mechanism for risk sharing. I utilize the economic link framework from Cohen and Frazzini (2008) and find evidence of risk sharing through the firm and customer (firm/customer) relationships over the period of 1980-2016, controlling for characteristics associated with factor risk and industry effects.

What drives the variation in asset pricing factor sensitivities? Figure 1 motivates this research question: If we calculate firms' factor sensitivities using a standard Fama and French (1993) three-factor model, and, for example, plot their "small minus big" (SMB) sensitivity against their (log) market value of equity, we see tremendous variation in SMB betas amongst similarly sized firms.[1] Intuitively, when I test this simple linear model (SMB beta on log size), I find the relationship between SMB beta and (log) market value of equity is negative

[1] These betas are calculated for firms that exist as of the end of December, 2016. Regressions are for the previous five years, with a minimum of two years of data available. The basic results hold over a variety of estimation techniques (all firms over all time, past two years, etc.)

and statistically significant (larger firms have less exposure to small stock risk). However, this basic test shows that less than 3% of the variation in SMB beta is explained by (log) market value of equity ($R^2 = 0.027$).

**Fig. 1. SMB Betas and MVE.** This figure plots SMB betas from the Fama and French (1993) 3-factor model for firms who existed on December 30, 2016. Regressions are run using five years of previous returns, with a minimum of two years of return data available. Firms' SMB betas are plotted against the natural logarithm of their market value of equity.

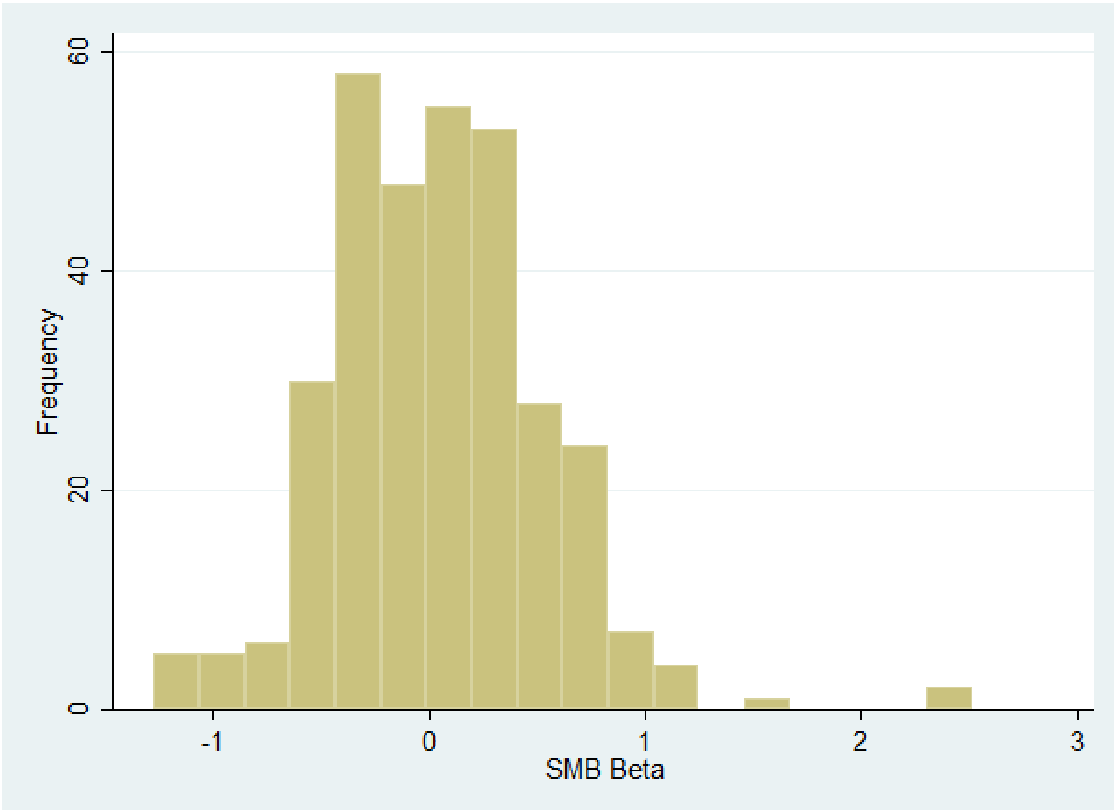



Further, figure 2 shows the distribution of SMB betas for the top 10% of firms[2]. Assuming that these firms are "comparably sized", we see that there are some firms with SMB betas of less than -1, and yet others with SMB betas greater than 1.

Figure 3 shows that the basic motivation is similar for "high minus low" (HML) factor sensitivities: If we plot firms' HML betas and their corresponding ratio of book value of equity to market value of equity (BE/ME), we see variation in HML betas for firms with

[2]The distributions look similar if we look at different deciles (i.e. smallest 10%) or if we calculate different quantiles (i.e. ventiles or percentiles).

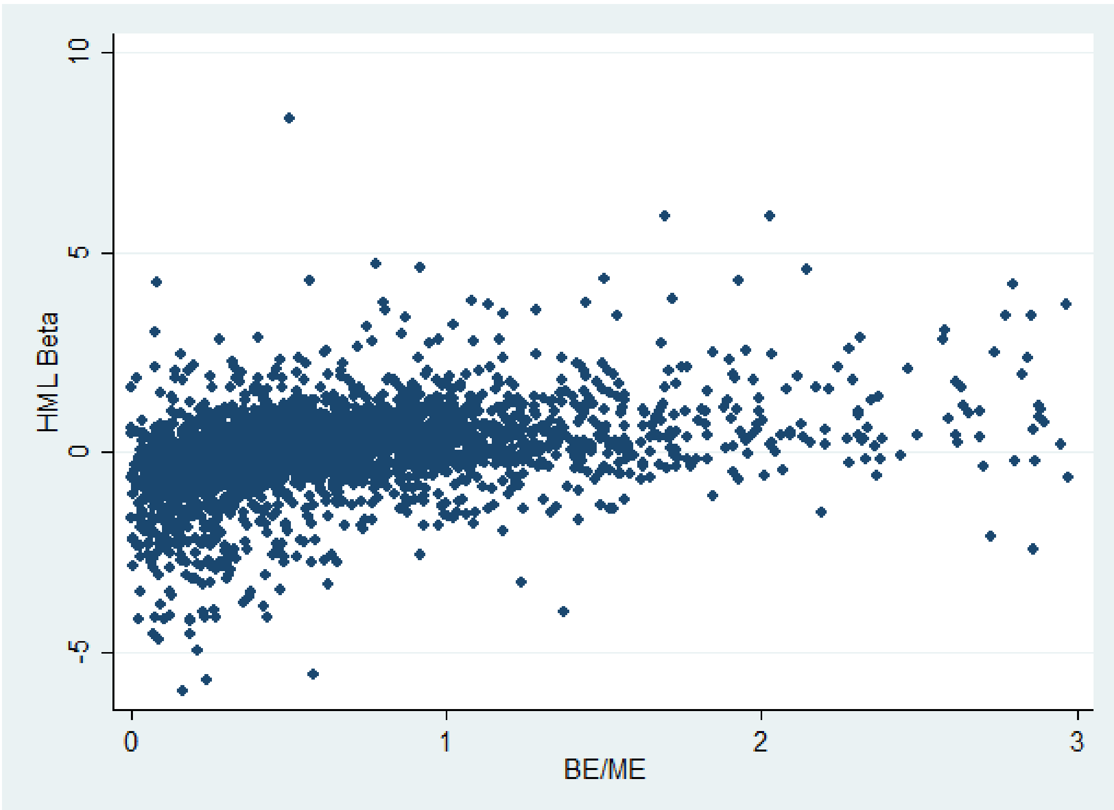
**Fig. 2. Distribution of SMB Betas for top 10% of firms by MVE**. This figure shows the distribution of SMB betas for the top 10% of firms, sorted by market value of equity, who existed on December 30, 2016. SMB betas are calculated from the Fama and French (1993) 3-factor model.




the same BE/ME. Intuitively, the relationship between HML beta and BE/ME is positive and statistically significant (firms with higher BE/ME (value firms) have more exposure to value risk). However, less than 5% of the variation in HML beta is explained by firms' book to market ratio ($R^2 = 0.045$).

What drives this variation? Certainly, we estimate these betas with noise. However, consider the distribution of SMB betas for the top decile of firms by size in figure 2: it would be unlikely that these firms' betas are all indistinguishable from one another. I hypothesize that firms share factor risks through their economic link of firm/customer relationships. Regulation SFAS No. 131 requires firms to disclose customer names who comprise more than 10% of their reported sales. I follow the methodology of Cohen and Frazzini (2008) and download

**Fig. 3. HML Betas and BE/ME.** This figure plots HML betas from the Fama and French (1993) 3-factor model for firms who existed on December 30, 2016. Regressions are run using five years of previous returns, with a minimum of two years of return data available. Firms' HML betas are plotted against the ratio of their book value of common equity to market value of equity, calculated as book common equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1$.




this customer data from Compustat segment files. I calculate factor sensitivities (SMB and HML betas) for each firm and customer for the reported fiscal year end firm/customer match. I control for known items that are associated with the factor sensitivities and industry effects, and find evidence of risk sharing through this economic link. There is a positive and statistically significant relationship between customers' SMB betas and firms' SMB betas. There is also a positive and statistically significant relationship between customers' HML betas and firms' HML betas. This paper adds to the literature by providing evidence of the propogation of factor risk through the firm/customer economic link.

## 1.2 Related literature

There is an extensive literature related to the size effect.[3] Banz (1981) provided some of the first evidence of the size effect in returns. Fama and French (1992a) show that the bottom size decile of firms earns higher returns than the top size decile. Subsequently, they attribute the size and value effects as proxies for common risk factors Fama and French (1993).

Berk (1995) provides a critique of the size effect. He argues that whenever there is a missing risk factor in the asset pricing model, size (market value of equity) will be negatively correlated with the missing factor. He shows that in a one period model with two firms facing the same end of period expected cash flow, if one firm is riskier, their market value will be lower and therefore have higher expected returns. Hence, the negative relation between size and expected returns. Of course, if size itself is not a systematic risk factor, and if we could perfectly observe all true systematic risk factors in our asset pricing model, then the size effect would disappear. However, if size is correlated to some unobserved systematic risk factor, then this critique is not relevant to my argument, since I am describing how this risk propogates through the economy through the firm/customer link.

Vassalou and Xing (2004) find that the size and book to market effects can be attributed to default risk. They use a measure of default risk similar to Merton (1974) and find that the size effect exists in the highest quintile of firms sorted on default risk. Similarly, they find that the book to market effect exists in the two highest quintiles of default risk. I calculate two proxies of default risk: standard deviation of return on assets (ROA), defined as earnings before interest, taxes, depreciation and amortization (EBITDA) and the KMV-Merton distance to default, which is similar to the Merton (1974) default risk measure. My results hold after controlling for the standard deviation of ROA.[4]

Chan and Hsieh (1985) uses Fama-MacBeth regressions to show that macroeconomic variables pick up the size effect. I control for changes in the macroeconomy by including

[3] See Van Dijk (2011) for a recent survey of the size literature.

[4] I am in the process of running the tests with the KMV-Merton measure.

changes in real gross domestic product growth as a control in my tests. My results remain after including this macroeconomic control, and they are robust to other macroeconomic controls (unreported).

Daniel and Titman (1997) find that the cross-sectional variance in stock returns is explained by characteristics, and not by the covariance structure of returns. They sort stocks into portfolios based on size and BE/ME, and show that "factor loadings do not explain the high returns associated with small and high book-to-market stocks beyond the extent to which they act as proxies for these characteristics." However, Berk (2000) criticizes their conclusions by suggesting their technique produces biased results.

This paper is closely related to Cohen and Frazzini (2008) and Cao and Lin (2016). Cohen and Frazzini (2008) use the same data over an earlier sample period and investor inattention as a mechanism to show evidence of return predictability across the firm/customer link. Cao and Lin (2016) use this same mechanism of investor inattention to show evidence of return predictability, but they use a different economic link. Instead of firm/customer links, they focus on strategic alliance. My approach is different from these papers in that I focus on the network effects on factor sensitivities, which has yet to be studied.

The rest of this paper proceeds as follows: Section 2 presents the data and describes the variables used in the analysis. Section 3 presents the results of different tests of network transmission of risk for the SMB and HML factors. Section 4 summarizes and provides questions for future study.

## 1.3 Data

The data come from several sources: return data for customers and suppliers come from the Center for Research in Security Prices (CRSP). Accounting information and firm/customer links come from Compustat. Market returns, risk free rates and factor returns are from Ken French's data website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Finally, macroeconomic data (real GDP growth rates) come from the Federal Reserve Economic Data (FRED) from the St. Louis Federal Reserve.

The sample period for all analyses is from January 1980 - December 2016. This period is selected because customer/supplier link data begin in January 1980. Data on firms' customers comes from Compustat segment files. Regulation SFAS No. 131 requires firms to report their customers' names who represent more than 10% of the total reported sales. Following Cohen and Frazzini (2008), I match customer names to their corresponding CRSP permnos. Since reported names are not consistently formated prior to 1998, I utilize Cohen and Frazzini (2008) matched dataset from Andrea Frazzini's data website (http://people.stern.nyu.edu/afrazzin/data_library.htm). This dataset provides firm/customer matches from 1980-2004. I update this dataset with my name-matching algorithm from 2005-2016. The final matched dataset includes 39,531 matched firms/customers from 1980-2016.

I calculate firm and customer factor sensitivities using Fama and French (1993) 3-factor asset pricing model:

$$R^e_{i,t} = \beta_0 + \beta_{MKT} R_{MKT,t} + \beta_{SMB} R_{SMB,t} + \beta_{HML} R_{HML,t} + \epsilon_{i,t} \tag{1}$$

where $R^e_{i,t}$ is the excess return of firm/customer $i$ at time $t$, and $R_{k,t}$ is the return of factor $k$ at time $t$ for $k \in \{MKT, SMB, HML\}$. Factor sensitivities are calculated as of the fiscal year-end date over the previous sixty months, with a minimum of two years of return data available in order to be included in the final sample. In order to ensure accounting data is known prior to returns being realized, book-to-market ratios are calculated in the standard, lagged fashion of book common equity for the fiscal year ending in calendar year $t-1$, divided by market value of equity at the end of December of $t-1$. The standard deviation of return on assets for firm/customer $i$ is calculated as the time series average of earnings before interest, taxes, depreciation, and amortization divided by total assets. Finally, industry adjusted factor sensitivities are calculated as the factor sensitivity for firm/customer $i$ at time $t$ minus the equally-weighted industry average factor sensitivity for each three digit SIC code.[5]

[5] As a robustness check, in the next version of this paper, I intend to calculate *value-weighted* industy

The main panel for the analysis includes 19,801 distinct firm-year customer relationships. Table 1 lists the descriptive statistics. The sample includes 13,199 unique firms and 7,334 unique customers. The average customer size is much larger than the average firm size (20 billion in market value of equity versus 2.2 billion). Cohen and Frazzini (2008) indicate this could an artifact of the data generating process, as larger firms are more likely to be above the 10% threshold when reporting of customer information is mandated. Median market betas are similar for firms and customers (1.04 and 1.05 respectively). Customers have lower exposure to SMB risk (0.24 median SMB beta versus 0.88 for firms), which is consistent with customers being larger on average, assuming a negative relationship between firm size and exposure to SMB risk. Customers also have lower book to market ratios (median of 0.28 versus 0.55 for firms) and HML betas (-0.46 versus 0.04), which is consistent with a positive relationship between book to market ratio and HML risk. The number of observations for book to market ratios decreases due to additional data restrictions, where firms must have positive book value of equity and data from the previous year for book equity and market equity.

Ideally, I would have data on every customer for each firm in the sample. This dataset is limited in that firms are only required to report customers who represent greater than 10% of their sales. This has the potential for biasing the results, especially considering that reported customers tend to be quite large as 1 shows. It is possible that these results are affected by these larger customers. Additionally, the matching algorithm for assigning permnos to customers had a low success rate. The full sample from Compustat contained over 200,000 firm/customer relationships. The sample before data restrictions included only approximately 40,000 observations, indicating only a 20% success rate. However, it is unlikely that there is anything systematically attributed to this poor success rate, which indicates the results will not be biased due to the poor match rate. Further data restrictions such as requiring two years of return data and lagged book value of equity further limit the sample.

adjusted customer factor sensitivities, using percentage of customer sales out of total sales as a value weight.

## 1.4 Results

I test the hypothesis that factor sensitivities are driven by network effects through firm and customer relationships. I do so in the context of linear regressions of the following type:

$$\beta_k^F = \gamma_0 + \gamma_1 x_k^C + \delta' \mathbf{z} + \epsilon \tag{2}$$

where $\beta_k^F$ is the firm factor sensitivity to factor $k$ for $k \in \{SMB, HML\}$, $x_k^C$ is the firm's customer's characteristic responsible for the risk sharing, and $\mathbf{z}$ is a vector of control variables.

### SMB Factor

I use three different customer characteristics to test whether SMB risk is shared through firm and customer relationships. First, I test the basic intuition of the effect of customer size on firm factor sensitivities. I control for firm size (the natural logarithm of market value of equity), since log market equity is negatively related to SMB betas.

Further, Vassalou and Xing (2004) suggest that the size effect is related to default risk. They create portfolios sorted on default risk, and find that the size effect is significant within the highest quintile. I control for firm default risk using two proxies: standard deviation of return on assets, calculated as the ratio of EBITDA to total assets, and distance to default using the KMV-Merton model[6], which the KMV Corporation developed from Merton's (1974) framework.

Chan and Hsieh (1985) find that the size effect is related to changes in the economic environment. I control for this by including real growth in gross domestic product as a proxy for changes in the economic environment. The results are robust to other macroeconomic measures as well (not reported). Finally, I include time (year) and firm fixed effects to

[6]SAS code for this calculation was used from Tyler Shumway's website: http://www-personal.umich.edu/~shumway/papers.dir/nuiter99_print.sas. This version of the paper only reports results using the standard deviation of ROA, as I am still calculating the distance to default results.

control for unobserved time and firm invariant factors. The first specification is:

$$\beta^F_{SMB} = \gamma_0 + \gamma_1 ln(MVE^C) + \gamma_2 ln(MVE^F) + \gamma_3 \sigma^F_{ROA} + \gamma_4 realGDPgrowth + FE + \epsilon \quad (3)$$

Table 2 lists the results of equation 3. In the base model of this specification where $\beta^F_{SMB}$ is regressed only on $ln(MVE^C)$, the coefficient on $\gamma_1$ is negative and statistically significant. This is consistent with the basic intuition that an increase in the size of customers leads to a decrease in the firm's sensitivity to the size effect. However, once the controls are added in the regression, this coefficient becomes weakly positive and is indistinguishable from zero. Therefore, I conclude that customer size does not affect firm's sensitivity to the size effect.

In the next specification, I test the effect of customer sensitivity to the SMB factor, $\beta^C_{SMB}$, on firm sensitivity to the SMB factor, $\beta^F_{SMB}$, controlling for the same items as above:

$$\beta^F_{SMB} = \gamma_0 + \gamma_1 \beta^C_{SMB} + \gamma_2 ln(MVE^F) + \gamma_3 \sigma^F_{ROA} + \gamma_4 realGDPgrowth + FE + \epsilon \quad (4)$$

Table 3 lists the results of this test. In this case, the coefficient on $\gamma_1$ is positive and economically and statistically significant at the 1% level. This result indicates that network effects are present in the propogation of SMB risk through firm/customer relationships.

Finally, I study whether customer industry effects impact the previous result. This seems unlikely since 85% of the firm/supplier links happen across industry instead of within industry. Nevertheless, I calculate industry adjusted customer SMB betas by subtracting average customer SMB betas by industry (3 digit SIC code) from individual customer betas: $\beta^C_{SMB} - \bar{\beta}^{Ind}_{SMB}$. Then, this industry adjusted customer SMB beta captures the pure size effect of an individual customer:

$$\beta^F_{SMB} = \gamma_0 + \gamma_1 \big(\beta^C_{SMB} - \bar{\beta}^{Ind}_{SMB}\big) + \gamma_2 ln(MVE^F) + \gamma_3 \sigma^F_{ROA} + \gamma_4 realGDPgrowth + FE + \epsilon \quad (5)$$

Table 4 lists the results from this test. As expected, there is little change in the coefficient estimate of $\gamma_1$ in this test. It remains statistically and economically significant and comparable to the previous test. In column 6 of 4 I also demean the dependent variable by the average firm SMB beta by industry, which is analagous to including industry fixed effects, and the results remain largely unchanged. As a result, I conclude that network effects are present in the propogation of SMB risk through firm/customer relationships.

## HML Factor

Similar to the SMB factor, I use three different customer characteristics to test whether HML risk is shared through firm and customer relationships. First, I test the basic intuition of the effect of customer BE/ME on firm factor sensitivities. I control for firm BE/ME (the ratio of firm book value of equity to market value of equity), since BE/ME is positively related to HML betas. I include the same controls as for the SMB factor:

$$\beta^F_{HML} = \gamma_0 + \gamma_1 \big(BE/ME\big)^C + \gamma_2 \big(BE/ME\big)^F + \gamma_3 \sigma^F_{ROA} + \gamma_4 realGDPgrowth + FE + \epsilon \tag{6}$$

Table 6 lists the results from this test. In the base model, the coefficient of interest is positive and statistically significant at the 1% level, which is consistent with the basic intuition that firms who sell to more value type customers (higher $\big(BE/ME\big)^C$) have higher sensitivity to the value effect ($\beta^F_{HML}$). As additional controls are included in the regression, the parameter estimate decreases in magnitude, but remains significant at the 10% level, which provides weak evidence of network effects in the propogation of HML risk through firm/customer relationships.

In the next specification, I test the effect of customer sensitivity to the HML factor,

$\beta^C_{HML}$, on firm sensitivity to the HML factor, $\beta^F_{HML}$, controlling for the same items as above:

$$\beta^F_{HML} = \gamma_0 + \gamma_1 \beta^C_{HML} + \gamma_2 \big(BE/ME\big)^F + \gamma_3 \sigma^F_{ROA} + \gamma_4 realGDPgrowth + FE + \epsilon \qquad (7)$$

Table 5 lists the results of this test. In this case, the coefficient on $\gamma_1$ is positive and economically and statistically significant at the 1% level. This result provides stronger evidence that network effects are present in the propogation of HML risk through firm/customer relationships.

Finally, I again consider whether customer industry effects impact the previous result, which is again unlikely since 85% of the firm/supplier links happen across industry instead of within industry. I calculate industry adjusted customer HML betas by subtracting average customer HML betas by industry (3 digit SIC code) from individual customer betas, which captures the pure value effect of an individual customer:

$$\beta^F_{HML} = \gamma_0 + \gamma_1 \big(\beta^C_{HML} - \bar{\beta}^{Ind}_{HML}\big) + \gamma_2 \big(BE/ME\big)^F + \gamma_3 \sigma^F_{ROA} + \gamma_4 realGDPgrowth + FE + \epsilon \qquad (8)$$

Table 7 lists the results from this test. As expected, there is little change in the coefficient estimate of $\gamma_1$ in this test. It remains statistically and economically significant and comparable to the previous test. In column 6 of 7 I also demean the dependent variable by the average firm HML beta by industry, and the results remain largely unchanged. As a result, I conclude that network effects are present in the propogation of HML risk through firm/customer relationships.

## 1.5 Conclusion

This paper investigates the variation in SMB and HML asset pricing factor sensitivities. For example, why do we see comparably sized firms with dramatically different sensitivities to SMB risk? This paper hypothesizes that this variation is associated with risk sharing through the economic link of firm/customer relationships. Regulation SFAS No. 131 requires firms to disclose customer names who comprise more than 10% of their reported sales. I create a dataset of firm and customer links, and find that firms' SMB and HML factor sensitivities are positively and significantly related to their customers' factor sensitivities, controlling for characteristics associated with these effects and industry adjustments. I conclude that this is evidence of propogation of factor risk across economically linked firms through firm and customer relationships. This paper adds to the literature by providing evidence of the propogation of factor risk through the firm/customer economic link.

These results are the first stage in this research project, and they introduce several other questions for further study. First, the results demonstrated here show that firm and customer factor loadings are *correlated*. In fact, when the analyses are run in the reverse order, such that *firm* betas explain *customer* betas, the results also hold. This suggests that firms and customers share their risk profiles with each other. What are the dynamics of the risk sharing? Consider a firm with an SMB beta of 0, who begins to sell to a customer with an SMB beta of 10. After one period, they share their risk and the firm increases their beta to 1 and the customer decreases their beta to 9. In the next period when they interact, they do so with different risk profiles, so that perhaps the firm now increases to 2 and the customer decreases to 8. How can we describe the dynamics of this? Further, what is the steady state (if it exists), and why do we settle here?

What are the dynamics of factor sensitivities within a firm? For example, do factor sensitivities change through product cycles such as when IBM transitioned from hardware into software? Or do these factor sensitivities change through acquisitions, for example when a firm with an SMB beta of 0 acquires a firm with an SMB beta of 10?

Further, do firms self-select customer/supplier relationships in order to achieve a target factor sensitivity? Consider a firm with an SMB beta of 10. Does this firm choose to sell to customers with low sensitivities to the SMB factor in order to mitigate their exposure to this factor?

Finally, does factor risk sharing occur through other economic links? For example, such as strategic alliance deals as in Cao and Lin (2016), or through joint ventures as in McConnell and Nantell (1985), or through shared analysts as in Muslu, Rebello, and Xu (2013)? The results in this paper suggest many new areas for future research.

**Table 1**
**Descriptive Statistics.** Betas are calculated from Fama and French 3-factor model regressions from the end of the fiscal year over the prior five years, with a minimum of two years of return data available. The ratio of the book value of common equity to market value of equity is calculated as book common equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1$.

Firms:

| Variable | n | Mean | S.D. | Min | Median | Max |
|---|---|---|---|---|---|---|
| MVE | 13,199 | 2.2B | 12B | 160K | 120M | 280B |
| $\beta^F_{MKT}$ | 13,199 | 1.10 | 0.83 | -5.87 | 1.04 | 8.74 |
| $\beta^F_{SMB}$ | 13,199 | 1.01 | 1.24 | -11.34 | 0.88 | 15.85 |
| $\beta^F_{HML}$ | 13,199 | -0.04 | 1.35 | -9.73 | 0.04 | 12.59 |
| BE/ME | 9,519 | 0.73 | 0.9 | 0.00 | 0.55 | 53.14 |

Customers:

| Variable | n | Mean | S.D. | Min | Median | Max |
|---|---|---|---|---|---|---|
| MVE | 7,334 | 20B | 49B | 520K | 3.7B | 640B |
| $\beta^C_{MKT}$ | 7,334 | 1.10 | 0.58 | -2.62 | 1.05 | 5.69 |
| $\beta^C_{SMB}$ | 7,334 | 0.39 | 0.90 | -3.00 | 0.24 | 6.45 |
| $\beta^C_{HML}$ | 7,334 | 0.03 | 0.97 | -6.45 | -0.46 | 0.08 |
| BE/ME | 6,581 | 0.61 | 0.50 | 0.00 | 0.28 | 0.49 |

**Table 2**

**The effect of customer (log) market value of equity on firm SMB betas.** This table presents results for the regression of firm SMB betas on customer (log) market value of equity and controls. $\beta^F_{SMB}$ is firm SMB betas calculated from Fama and French 3-factor model regressions from the end of the fiscal year over the prior five years, with a minimum of two years of return data available. $ln(MVE^F)$ and $ln(MVE^C)$ are the natural logarithm of firm and customer respectively market value of equity. $\sigma_{ROA}$ is the standard deviation of firm return on assets, calculated as earnings before interest and taxes, depreciation and amortization divided by total firm assets. "real gdp growth" is a macro control variable, calculated as the annual real growth rate in gross domestic product.

| | (1) $\beta^F_{SMB}$ | (2) $\beta^F_{SMB}$ | (3) $\beta^F_{SMB}$ | (4) $\beta^F_{SMB}$ | (5) $\beta^F_{SMB}$ |
|---|---|---|---|---|---|
| $ln(MVE^C)$ | -0.042*** | -0.004 | -0.001 | -0.001 | 0.002 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) |
| $ln(MVE^F)$ | | -0.111*** | -0.120*** | -0.120*** | 0.017 |
| | | (0.004) | (0.004) | (0.004) | (0.011) |
| $\sigma_{ROA}$ | | | 0.130*** | 0.130*** | |
| | | | (0.028) | (0.028) | |
| real gdp growth | | | | 0.010* | |
| | | | | (0.005) | |
| Constant | 1.957*** | 3.179*** | 3.295*** | 3.248*** | |
| | (0.092) | (0.099) | (0.117) | (0.119) | |
| Year/Firm FE? | N | N | N | N | Y |
| $N$ | 19801 | 19801 | 15000 | 15000 | 14564 |
| adj. $R^2$ | 0.005 | 0.047 | 0.056 | 0.056 | 0.592 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 3**

**The effect of customer SMB betas on firm SMB betas.** This table presents results for the regression of firm SMB betas on customer SMB betas and controls. $\beta^F_{SMB}$ and $\beta^C_{SMB}$ are firm and customer, respectively, SMB betas calculated from Fama and French 3-factor model regressions from the end of the fiscal year over the prior five years, with a minimum of two years of return data available. $ln(MVE^F)$ is the natural logarithm of firm market value of equity. $\sigma_{ROA}$ is the standard deviation of firm return on assets, calculated as earnings before interest and taxes, depreciation and amortization divided by total firm assets. "real gdp growth" is a macro control variable, calculated as the annual real growth rate in gross domestic product.

| | (1)<br>$\beta^F_{SMB}$ | (2)<br>$\beta^F_{SMB}$ | (3)<br>$\beta^F_{SMB}$ | (4)<br>$\beta^F_{SMB}$ | (5)<br>$\beta^F_{SMB}$ |
|---|---|---|---|---|---|
| $\beta^C_{SMB}$ | 0.178*** | 0.159*** | 0.165*** | 0.167*** | 0.087*** |
| | (0.011) | (0.011) | (0.012) | (0.012) | (0.011) |
| $ln(MVE^F)$ | | -0.109*** | -0.119*** | -0.118*** | 0.018 |
| | | (0.004) | (0.004) | (0.004) | (0.011) |
| $\sigma_{ROA}$ | | | 0.123*** | 0.123*** | |
| | | | (0.027) | (0.027) | |
| real gdp growth | | | | 0.014** | |
| | | | | (0.005) | |
| Constant | 0.965*** | 3.037*** | 3.219*** | 3.160*** | |
| | (0.009) | (0.068) | (0.082) | (0.085) | |
| Year/Firm FE? | N | N | N | N | Y |
| $N$ | 19801 | 19801 | 15000 | 15000 | 14564 |
| adj. $R^2$ | 0.013 | 0.057 | 0.068 | 0.068 | 0.594 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 4**

**The effect of customer industry adjusted SMB betas on firm SMB betas.** This table presents results for the regression of firm SMB betas on customer industry adjusted SMB betas and controls. $\beta^F_{SMB}$ and $\beta^C_{SMB}$ are firm and customer, respectively, SMB betas calculated from Fama and French 3-factor model regressions from the end of the fiscal year over the prior five years, with a minimum of two years of return data available. $\bar{\beta}^{Ind}_{SMB}$ is the equally weighted average industry SMB beta. $ln(MVE^F)$ is the natural logarithm of firm market value of equity. $\sigma_{ROA}$ is the standard deviation of firm return on assets, calculated as earnings before interest and taxes, depreciation and amortization divided by total firm assets. "real gdp growth" is a macro control variable, calculated as the annual real growth rate in gross domestic product.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\beta^F_{SMB}$ | $\beta^F_{SMB}$ | $\beta^F_{SMB}$ | $\beta^F_{SMB}$ | $\beta^F_{SMB}$ | $\beta^F_{SMB} - \bar{\beta}^{Ind}_{SMB}$ |
| $\beta^C_{SMB} - \bar{\beta}^{Ind}_{SMB}$ | 0.160*** | 0.146*** | 0.138*** | 0.140*** | 0.086*** | 0.087*** |
| | (0.013) | (0.012) | (0.014) | (0.014) | (0.012) | (0.012) |
| $ln(MVE^F)$ | | -0.110*** | -0.120*** | -0.119*** | 0.017 | 0.015 |
| | | (0.004) | (0.004) | (0.004) | (0.011) | (0.011) |
| $\sigma_{ROA}$ | | | 0.127*** | 0.127*** | | |
| | | | (0.027) | (0.027) | | |
| real gdp growth | | | | 0.013* | | |
| | | | | (0.005) | | |
| Constant | 0.994*** | 3.088*** | 3.267*** | 3.214*** | | |
| | (0.008) | (0.068) | (0.082) | (0.085) | | |
| Year/Firm FE? | N | N | N | N | Y | Y |
| $N$ | 19801 | 19801 | 15000 | 15000 | 14564 | 14564 |
| adj. $R^2$ | 0.008 | 0.054 | 0.062 | 0.063 | 0.594 | 0.541 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 5**

**The effect of customer HML betas on firm HML betas.** This table presents results for the regression of firm HML betas on customer HML betas and controls. $\beta^F_{HML}$ and $\beta^C_{HML}$ are firm and customer, respectively, HML betas calculated from Fama and French 3-factor model regressions from the end of the fiscal year over the prior five years, with a minimum of two years of return data available. $BE/ME^F$ is the ratio of firm book value of common equity to market value of equity calculated as book common equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1$.$\sigma_{ROA}$ is the standard deviation of firm return on assets, calculated as earnings before interest and taxes, depreciation and amortization divided by total firm assets. "real gdp growth" is a macro control variable, calculated as the annual real growth rate in gross domestic product.

| | (1)<br>$\beta^F_{HML}$ | (2)<br>$\beta^F_{HML}$ | (3)<br>$\beta^F_{HML}$ | (4)<br>$\beta^F_{HML}$ | (5)<br>$\beta^F_{HML}$ |
|---|---|---|---|---|---|
| $\beta^C_{HML}$ | 0.365*** | 0.406*** | 0.403*** | 0.403*** | 0.147*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| $BE/ME^F$ | | 0.164*** | 0.161*** | 0.162*** | 0.041*** |
| | | (0.012) | (0.012) | (0.012) | (0.011) |
| $\sigma_{ROA}$ | | | -0.181*** | -0.181*** | |
| | | | (0.029) | (0.029) | |
| real gdp growth | | | | 0.003 | |
| | | | | (0.005) | |
| Constant | -0.072*** | -0.222*** | -0.200*** | -0.207*** | |
| | (0.009) | (0.013) | (0.013) | (0.019) | |
| Year/Firm FE? | N | N | N | N | Y |
| $N$ | 19801 | 14542 | 14534 | 14534 | 14101 |
| adj. $R^2$ | 0.056 | 0.097 | 0.099 | 0.099 | 0.629 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 6**

**The effect of customer book-to-market ratios on firm HML betas.** This table presents results for the regression of firm HML betas on customer book to market ratios and controls. $\beta^F_{HML}$ is firm HML betas calculated from Fama and French 3-factor model regressions from the end of the fiscal year over the prior five years, with a minimum of two years of return data available. $BE/ME^F$ and $BE/ME^C$ are the ratio of firm and customer respectively book value of common equity to market value of equity calculated as book common equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1.\sigma_{ROA}$ is the standard deviation of firm return on assets, calculated as earnings before interest and taxes, depreciation and amortization divided by total firm assets. "real gdp growth" is a macro control variable, calculated as the annual real growth rate in gross domestic product.

| | (1)<br>$\beta^F_{HML}$ | (2)<br>$\beta^F_{HML}$ | (3)<br>$\beta^F_{HML}$ | (4)<br>$\beta^F_{HML}$ | (5)<br>$\beta^F_{HML}$ |
|---|---|---|---|---|---|
| $BE/ME^C$ | 0.151*** | 0.128*** | 0.125*** | 0.129*** | 0.038* |
| | (0.018) | (0.019) | (0.019) | (0.019) | (0.019) |
| $BE/ME^F$ | | 0.191*** | 0.188*** | 0.190*** | 0.042*** |
| | | (0.013) | (0.013) | (0.013) | (0.011) |
| $\sigma_{ROA}$ | | | -0.226*** | -0.225*** | |
| | | | (0.032) | (0.032) | |
| real gdp growth | | | | 0.016** | |
| | | | | (0.006) | |
| Constant | -0.126*** | -0.274*** | -0.246*** | -0.289*** | |
| | (0.015) | (0.017) | (0.017) | (0.024) | |
| Year/Firm FE? | N | N | N | N | Y |
| $N$ | 17923 | 13607 | 13599 | 13599 | 13173 |
| adj. $R^2$ | 0.004 | 0.022 | 0.026 | 0.026 | 0.629 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 7**

**The effect of customer industry adjusted HML betas on firm HML betas.** This table presents results for the regression of firm HML betas on customer industry adjusted HML betas and controls. $\beta^F_{HML}$ and $\beta^C_{HML}$ are firm and customer, respectively, HML betas calculated from Fama and French 3-factor model regressions from the end of the fiscal year over the prior five years, with a minimum of two years of return data available. $\bar{\beta}^{Ind}_{HML}$ is the equally weighted average industry HML beta. $BE/ME^F$ is the ratio of firm book value of common equity to market value of equity calculated as book common equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1$. $\sigma_{ROA}$ is the standard deviation of firm return on assets, calculated as earnings before interest and taxes, depreciation and amortization divided by total firm assets. "real gdp growth" is a macro control variable, calculated as the annual real growth rate in gross domestic product.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\beta^F_{HML}$ | $\beta^F_{HML}$ | $\beta^F_{HML}$ | $\beta^F_{HML}$ | $\beta^F_{HML}$ | $\beta^F_{HML} - \bar{\beta}^{Ind}_{HML}$ |
| $\beta^C_{HML} - \bar{\beta}^{Ind}_{HML}$ | 0.237*** | 0.276*** | 0.276*** | 0.275*** | 0.157*** | 0.156*** |
| | (0.013) | (0.014) | (0.014) | (0.014) | (0.011) | (0.012) |
| $BE/ME^F$ | | 0.190*** | 0.187*** | 0.188*** | 0.041*** | 0.044*** |
| | | (0.012) | (0.012) | (0.012) | (0.011) | (0.011) |
| $\sigma_{ROA}$ | | | -0.216*** | -0.216*** | | |
| | | | (0.030) | (0.030) | | |
| real gdp growth | | | | 0.008 | | |
| | | | | (0.006) | | |
| Constant | -0.027** | -0.190*** | -0.164*** | -0.186*** | | |
| | (0.009) | (0.013) | (0.013) | (0.020) | | |
| Year/Firm FE? | N | N | N | N | Y | Y |
| $N$ | 19451 | 14542 | 14534 | 14534 | 14101 | 14101 |
| adj. $R^2$ | 0.017 | 0.044 | 0.047 | 0.047 | 0.629 | 0.530 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# Chapter 2

# More than 100% of the equity premium: How much is really earned on macroeconomic announcement days?

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## 2.1 Introduction

The return for bearing risk should be earned when the resolution of the risk is expected. If this expected resolution is concentrated on macroeconomic announcement days, then the expected returns should be higher on those days. A large literature confirms this concentration. Savor and Wilson (2013) show that about 60% of the equity risk premium is earned on the days when unemployment, inflation and interest rates are announced. Lucca and Moench (2015) show that about 80% of the equity premium is earned during the 24 hours prior to interest rate announcements by the FOMC. Cieslak et al. (2019) show that the entire equity premium is earned on a bi-weekly cycle of the FOMC announcements.

60%, 80% and 100% suggest there is an adding-up problem across these studies. Table 8 verifies that one can earn about 150% of the equity premium by holding the market on all of the expected news days identified by the above three papers. This too-much-return puzzle is not due to an error, an artifact of different samples, or overlapping announcements. Moreover, we show this puzzle is robust: many sets of macroeconomic announcements earn more than 100% of the equity premium.[7]

Earning more than 100% of the equity premium on a small set of pre-scheduled announcement days is puzzling for many reasons. It implies that holding the market during the majority of the year earns predictably negative returns. It leaves no room for any other

[7] We focus on the announcement days themselves, setting aside issues of pre-announcement drift, which would make the concentrations even larger. See Kurov et al. (2019) for evidence of pre-announcement drifts beyond the FOMC.

**Table 8**
**Equity Premium Concentration from Combining Prior Papers** The first column reports the average market excess return on the expected news days from the prior literature: inflation (PPI), employment, and FOMC days from Savor and Wilson (2013); the day prior to the FOMC days from Lucca and Moench (2015); and days -1 to 3, 9 to 13, 19 to 23, and 29 to 33 in FOMC cycle time from Cieslak et al. (2019). The second column reports the average market excess return on all other days. The third column reports the difference between the two. We also report the number of observations in each sample and the percent of the equity premium earned on the announcement days, which is calculated per Equation 9. The sample period is January 1990 to June 2018. Standard errors are in parentheses, and *, ** and *** indicate significance at the 10, 5 and 1 percent levels.

| | Ann. | Non-ann. | Diff. |
|---|---|---|---|
| Average market excess return | 7.7*** | -1.9 | 9.6*** |
| | (1.79) | (1.71) | (2.49) |
| $N$ | 3,820 | 3,615 | |
| Percent of equity premium | 149.1% | | |

systematically important news events such as earnings announcements, revelations about a pandemic and government responses to it, or other periods of heightened uncertainty.[8] It contrasts with the literature's risk based measures that show macroeconomic news explains only a small fraction of market returns (Cutler et al., 1989). It creates the complementary puzzle of excessively high Sharpe ratios on announcement days, because consistent with Cutler et al. (1989) announcement and non-announcement days show similar amounts of risk (Savor and Wilson, 2013; Ai and Bansal, 2018).

Though theory predicts high returns on important macroeconomic announcement days, important days cannot be identified from high returns. High returns lack this identifying power because they could be due either to high expected returns or positive ex-post noise realizations. Though individual papers acknowledge this division to varying degrees, these papers have inspired a literature focusing on the expected return interpretation. This literature attempts to rationalize this high expected returns with among other things new utility functions and new measures of risk (e.g., Ai and Bansal, 2018; Hu et al., 2019b). Papers rationalizing their findings with the ex-post noise explanation face a Catch-22. If noise

[8]Many papers document the systematic importance of earnings announcements: Frazzini and Lamont (2007); Barth and So (2014); Savor (2012); Barber et al. (2013); McLean and Pontiff (2016); Gilbert et al. (2018); Savor and Wilson (2016); Linnainmaa and Zhang (2019). Hu et al. (2019a) show that eight heightened-uncertainty days per year account for more than 30% of the equity premium.

drives the equity premium concentrations they identify on macroeconomic announcement days, then these concentrations neither reveal the expected returns due to macroeconomic announcements nor serve as a test of these announcement series' importance.

In essence, either the rest of the year earns negative expected returns or the extraordinary concentration of the equity premium on these small sets of announcements must be due to inadvertent sample selection. This need not be a selection bias of individual researchers. It may well be driven by the publication process itself (Harvey, 2017; Andrews and Kasy, 2019). Indeed, we show there are many other combinations of macroeconomic variables that lead to an even greater concentration of the equity premium than those documented in the literature. The existence of such "better" alternative combinations suggests that researchers did not produce their results by explicitly data-mining.

To salvage the expected return interpretation, one might ignore the too-much return problem and argue that variables used like unemployment, inflation and the FOMC could have been ex-ante identified as important. The danger is that even the impression that these variables are ex-ante important can be contaminated by their ex-post high returns. Friedman (1953) writes:

> The facts that serve as a test of the implications of a hypothesis might equally well have been among the raw material used to construct it [...] the process [of hypothesis construction] never begins from scratch [...] the two methodologically distinct stages [of hypothesis construction and testing] are always proceeding jointly.

In this vein, seeing that the construction spending announcement series has the highest returns and risk in the sample, one might be prompted to argue for its ex-ante importance based on housing accounting for roughly 20% of GDP. That another could simply call this ex-post story telling, exemplifies that debating ex-post what is ex-ante important is unlikely to lead to satisfying conclusions.[9]

[9]Resorting to reduced form models as support for specific macroeconomic announcements is problematic when matching models to the data. In reality each macroeconomic series is inherently tied to the others via equilibrium conditions. Hence every announcement implicitly reveals information about all the other series.

Acknowledging the inability to identify ex-ante the important from unimportant macroeconomic announcements, we avoid this selection bias by using the entire set of plausibly similarly important announcements to average out the noise. To minimize the chance of accidentally selecting a sample made up of only ex-post important macroeconomic announcements, we analyze all U.S. monthly macroeconomic variables and the FOMC. The intuition for this solution builds on the work of Fama and French (2010) and Kelly and Jiang (2014) that widening the cross-section can substitute for longer time-series.[10]

We support this argument for ex-ante similarity in two ways. First, we show the similarity of realized volatility, VIX and trading volume across these days. Second, with a simulation we show that both the variation in realized returns across these announcements and the extreme concentration of the equity premium in a few series are consistent with all the announcements being ex-ante indentical. This simulation shows that while the data lacks sufficient information to identify the *number* of important macroeconomic announcements, we can nevertheless reliability identify the fraction of the equity premium attributable to all macroeconomic announcements. The key is to use a large set of possible announcement series. Moreover, this identification is robust to the inclusion of unimportant announcements, but not robust to focusing on small sets of announcement with high ex-post returns.

Focusing on small sets of announcements is the first source of the too-much return puzzle. The second source is the fact that macroeconomic announcements cluster in time, such as near the beginning or end of the month. These periods have previously been associated with high returns due to many sources such as other information flows, monthly payment cycles and capital market inflows.[11] To control for this timing effect, we exploit the variation

Therefore the separate importance of each series is poorly defined. This can be seen by the fact that the time ordering of announcements affects financial market's interpreation of the announcements (e.g., Gilbert et al., 2012).

[10]Fama and French (2010) show in the context of mutual fund managers that one can avoid the multiple comparison test and selection bias of looking at ex-post successful managers by looking at the entire cross-sectional distribution of managers. Kelly and Jiang (2014) show that one can help solve the problem of short time-series, by using the information in the cross-section of similar events to effectively extend the time-series sample.

[11]See for example Chambers and Penman (1984); French and Roll (1986); Penman (1987); Jacobs and Levy (1988); Ogden (1990); Meng and Pantzalis (2018); Etula et al. (2019)

in the timing across and within months of the macroeconomic announcements. The identification comes from the prediction that if the expected news from announcements drives higher expected returns, those expected returns should move and accompany the expected announcements throughout the month.

We can thus isolate the effect of news due to macroeconomic announcements from other seasonal sources that drive returns by regressing the market's daily excess returns on fixed effects for macroeconomic announcement days along with fixed effects for the day-of-the-month. Omitting the day-of-month fixed effects imposes the unrealistic assumption that all days of the month are expected to yield the same information with the only difference between days coming from the presence of a macroeconomic announcement. We find the day-of-month fixed effects are jointly statistically significant. In contrast we find the fixed effect for macroeconomic announcements is not. This statistical insignificance is consistent with our argument that the findings of the prior literature can be attributed to sample selection issues.

Nevertheless, since statistical significance is more sensitive to the inclusion of extra unimportant announcements than is the expected value of the point estimate, we give the prior literature the benefit of the doubt and focus on these point estimates.[12] The point estimate for the macroeconomic announcements fixed effect is econonmically significant. We find *as a whole* macroeconomic announcements are responsible for 58% of the equity premium.

This point estimate is consistent with the concentration hypothesis, but being much less than 100% of the equity premium, leaves room for the many other plausibly important sources of information in the economy to contribute to the equity premium. With the larger set of announcement series considered, this premium is earned over 62% of days rather than a tiny fraction of days considered by the previous literature. That it is earned over many days, means the small increases in risk observed on macroeconomic announcement days can explain this observed premium. This helps solve the puzzle of excessively high Sharpe ratios,

[12] In the context of return predictability regressions, Cochrane (2007) makes the related point that the economic significance of a point estimate is different from its statistical significance.

which prior work found to be an order of magnitude higher on "selected" macroeconomic announcement days compared to non-announcement days (Savor and Wilson, 2013; Ai and Bansal, 2018). Consistent with this finding, our simulation results caution against looking at Sharpe ratios for subsets of announcement series with ex-post high returns. The caution comes from ex-post returns providing little to no information on the number of important announcement series.

Though we argue for considering all the macroeconomic announcement series jointly, we show our findings are robust to a variety of alternative specifications. This includes using a separate fixed effect for each macroeconomic announcement series. In that case, the identification comes from the variation in the timing of each announcement series across months. These 21 fixed effects are jointly statistically insignificant, though their point estimates continue to show a concentration of the equity premium in macroeconomic announcements as a whole. The only fixed effect statistically significant on its own is that for the FOMC announcements. Caution is warranted in concluding from this that the FOMC is special. As is implicit in the joint test of significance, 1 of 21 announcement series being statistically significant is what one would expect from a multiple comparison problem. Moreover, simulations show the concentration of the equity premium in the FOMC announcements is consistent with what one would expect were all 21 announcement series ex-ante identical.

A related literature finds the *slope* in CAPM regressions on subsets of macroeconomic announcements is larger on FOMC, unemployement and inflation announcement days than on non-announcement days (Savor and Wilson, 2014).[13] The literature's interpretation is that the CAPM fits better on these days revealing a fundamentally different risk return relationship on the announcement days that supports the specialness of these announcements.

We derive that these slopes provide the same information as the realized market return on announcement days. We illustrate the mechanical connection between the realized market return and these CAPM slopes in two ways. First, we show across all combinations of 2

[13] This is related to Andrei et al. (2018) as well.

or 3 macroeconomic announcement series the CAPM slopes vary essential 1-to-1 with their realized market returns. Second, we sort days into deciles based on the realized market return and find a monotonically increasing CAPM slope. Thus these larger slopes neither show a better fit of the CAPM on announcement days (consistent with the similar pricing errors across non-announcement and announcement days), nor show additional specialness of announcement days.

Our paper is related to a growing literature on the multiple comparisons problem or p-hacking in asset pricing (see Harvey et al. (2015); Harvey and Liu (2018); Chordia et al. (2019); Heath et al. (2020), among others). As researchers search for statistically significant anomalies in the same CRSP data set, one cannot consider each hypothesis test as fully independent of the previous test. Eventually, significance will be obtained due to random sampling error or in this context one will find a set of macroeconomic announcement with very high returns.

After controlling for sample selection and day-of-the-month return patterns, macroeconomic announcement days are not as special as the prior literature suggests. Though point estimates suggest a concentration of the equity premium on macroeconomic announcement days, statistically these days look relatively normal. A large literature has developed new models and methods to explain the high premia (and even pre-announcement drifts) documented on some macroeconomic announcement days (Ai and Bansal, 2018; Ai et al., 2018; Wachter and Zhu, 2018; Andrei et al., 2018). Our message is that perhaps there is no puzzle to solve, and therefore the need for new preferences, new learning processes and even new measures of risk should be reevaluated.

## 2.2 Data

To capture the distribution of an entire set of ex-ante hypothesized important macroeconomic announcements, we construct a panel of the announcement dates from January 1990 to June 2018 for all major U.S. macroeconomic series that are released at the monthly frequency.

Because of its near-monthly frequency and common inclusion in the literature, we also include the FOMC announcement dates. Table 9 lists the included series, the announcing agency, the start and end date of the series in our sample and the number of announcements for the series. This data set of macroeconomic variables mirrors the prior literature (Andersen et al., 2003, 2007; Gilbert et al., 2017) but excludes weekly jobless claims and quarterly GDP announcements.

Many economic statistics are released on the same day, e.g., the release of the unemployment rate by the Bureau of Labor Statistics on the first Friday of every month at 8:30am ET includes non-farm payroll and hourly earnings. We list the announcement by only one of the series announced on that day. Hence one set of announcement dates in our analysis can cover multiple macroeconomic variables released at the same time by the same (or another) agency. Since our objective is to capture the information for all major macroeconomic announcements and the *total* contribution of all macroeconomic news announcements to the equity premium, this inability to separately identify the effect of a given variable announced on a given day is not problematic.

## 2.3 Individual Announcement Equity Premium Concentration

For each macroeconomic announcement series, we calculate the percent of the equity premium that each macroeconomic variable accounts for over the sample period. This is computed as the annualized return to a portfolio that invests in the market on the announcement days and invests in the risk-free asset on all other days:

$$\frac{\left(\prod_{t=1}^{N_i}(1+r_{m,t}^{e,i})\right)^{\frac{252}{T}}-1}{\left(\prod_{t=1}^{T}(1+r_{m,t}^{e})\right)^{\frac{252}{T}}-1} \tag{9}$$

where $T$ is the total number of days in the sample and $r^{e,i}_{m,t}$ represents the market's excess return on days when variable $i$ is released.[14] The daily market return $r_{m,t}$ is the CRSP value-weighted return including distributions, the risk-free rate $r_{f,t}$ is the one-month Treasury bill rate from Kenneth French's website, and hence the market's excess return is $r^{e}_{m,t} = r_{m,t} - r_{f,t}$. Over our sample period, the market's average daily excess return is 3.2 basis points and its daily volatility is 109 basis points.

[14]The ratio of the total cumulative returns over the entire sample period without annualizing is

$$\left(\left(\prod_{t=1}^{N_i}(1+r^{e,i}_{m,t})\right)-1\right) \Big/ \left(\left(\prod_{t=1}^{T}(1+r^{e}_{m,t})\right)-1\right).$$

**Table 9**

**Monthly Macroeconomic Announcements** This table lists the 21 macroeconomic variables, the agencies that release them, the start and end dates of the series within the sample, and the number of announcements for each series. The variables are listed in descending order of the percent of the annualized equity premium earned on a portfolio that invests in the CRSP value-weighted market index on the announcement day and in the risk-free asset on all other days (see Equation 9). Realized standard deviation is the annualized standard deviation of the excess market return on the announcement days for each series. VIX is the average value of VIX the day before each announcement. Trading volume is the average dollar weighted trading volume of all NYSE stocks on the announcement days. Weights are determined by closing prices on the day prior to the announcement. All series are monthly except for the FOMC.

| Variable | Agency | Start Date | End Date | N | % of EP | Realized Std. Dev. | VIX | Trading Volume |
|---:|---:|---:|---:|---:|---:|---:|---:|---:|
| Consturction Spending | Census Bureau | 1/2/1990 | 6/1/2018 | 340 | 36.2% | 19.7% | 19.34 | 71.45 |
| FOMC | Federal Reserve | 2/8/1990 | 6/13/2018 | 228 | 31.9% | 17.3% | 19.68 | 75.67 |
| NAPM | Institute for Supply Management | 2/1/1990 | 6/1/2018 | 341 | 29.2% | 19.5% | 19.36 | 71.01 |
| Consumer Confidence | The Conference Board | 7/30/1991 | 6/26/2018 | 324 | 18.8% | 18.2% | 19.29 | 72.31 |
| New Home Sales | Census Bureau | 1/3/1990 | 6/25/2018 | 339 | 16.6% | 15.8% | 19.27 | 67.84 |
| Housing Starts | Census Bureau | 1/18/1990 | 6/19/2018 | 339 | 16.0% | 17.8% | 19.40 | 73.15 |
| Unemployment Rate | Bureau of Labor Statistics | 1/5/1990 | 6/1/2018 | 335 | 14.3% | 17.8% | 19.49 | 69.08 |
| UM Consumer Confidence F | University of Michigan | 2/1/1991 | 6/29/2018 | 327 | 13.3% | 15.6% | 18.97 | 71.23 |
| Producer Price Index | Bureau of Labor Statistics | 1/12/1990 | 6/13/2018 | 340 | 12.9% | 17.7% | 19.52 | 69.34 |
| Advance Retail Sales | Census Bureau | 1/12/1990 | 6/14/2018 | 340 | 12.4% | 17.9% | 19.43 | 69.15 |
| Durable Goods Orders | Census Bureau | 1/26/1990 | 6/27/2018 | 341 | 12.1% | 15.5% | 19.17 | 68.63 |
| Personal Consumption | Bureau of Economic Analysis | 1/29/1990 | 6/29/2018 | 337 | 11.2% | 17.4% | 19.13 | 69.13 |
| Capacity Utilization | Federal Reserve | 1/17/1990 | 6/15/2018 | 339 | 10.1% | 16.4% | 19.37 | 72.40 |
| Factory Orders | Census Bureau | 1/5/1990 | 6/4/2018 | 341 | 6.5% | 16.2% | 19.28 | 70.80 |
| Consumer Price Index | Bureau of Labor Statistics | 1/18/1990 | 6/12/2018 | 340 | 6.3% | 18.0% | 19.53 | 72.47 |
| Trade Balance | Census Bureau | 1/17/1990 | 6/6/2018 | 341 | 6.1% | 17.2% | 19.38 | 71.05 |
| Business Inventories | Census Bureau | 1/16/1990 | 6/14/2018 | 338 | -0.2% | 19.2% | 19.39 | 69.63 |
| Leading Indicators | The Conference Board | 1/31/1990 | 6/21/2018 | 341 | -0.4% | 18.3% | 19.29 | 72.33 |
| UM Consumer Confidence P | University of Michigan | 1/18/1991 | 6/15/2018 | 327 | -5.7% | 16.2% | 19.18 | 74.45 |
| Monthly Budget Statement | Bureau of the Fiscal Service | 2/22/1990 | 6/12/2018 | 334 | -7.7% | 17.3% | 19.19 | 69.80 |
| Consumer Credit | Federal Reserve | 1/8/1990 | 6/7/2018 | 339 | -7.9% | 16.0% | 19.56 | 70.17 |

The macroeconomic announcements in Table 9 are sorted in descending order of their ex-post "importance" as measured by this concentration of the equity premium. We see that there is a wide heterogeneity across macroeconomic variables. Construction spending and the FOMC each account for more than 30% of the equity premium.[15] Others, like consumer credit and the monthly budget statement, earn negative returns and hence represent a negative percentage of the equity premium. Taken at face value, without adjusting for their ex-post nature, these negative returns would say this subset of macroeconomic announcements earn negative expected returns and therefore provide a hedge for the risk in the economy.

The conclusion based on average realized returns that no systematically important news releases are ever expected to occur on non-announcement days is problematic and inconsistent with the history. Most recently, the market has responded dramatically to news about the COVID-19 pandemic on non-macroeconomic announcement days and the FED made many unscheduled announcements about new pandemic response policies that moved the market. Historically many of the largest market moves are unaccompanied by any macroeconomic news related to inflation, interest rates and industrial production, among others Cutler et al. (1989). That investors would not worry about the possibility of such moves on non-announcement days and demand compensation in terms of positive expected returns is implausible.

What then can explain the negative average returns not only on non-announcement days but even on 25% of macroeconomic announcement days? Explaining these as negative expected returns is difficult to reconcile with standard models of risk and return. These negative average returns are more easily explained by realized returns being a combination of expected returns and ex-post surprises. Given the volatility of the market returns, these ex-post surprises can easily swing the realized return of individual or even small sets of macroeconomic announcement days. (See Section ??.) Averaging across larger sets of

[15]Note that this percentage only includes the announcement day, and not the day before as in Lucca and Moench (2015) or the entire week as in Cieslak et al. (2019).

these announcements can help eliminate these surprises and provide a better measure of the expected returns on macroeconomic announcement days.

## 2.4 Risk is Similar Across All Macroeconomic Announcements

This leaves the question of which announcements to include. Unfortunately, using realized returns provides virtually no information as to the relative importance of these announcements. One possibility is to look at measures of risk such as realized volatility, VIX or trading volume to distinguish between the importance of macroeconomic announcements. Such risk measures are less easily biased by unexpected positive or negative news than are realized returns.

In Table 9 we see that the realized volatility on macroeconomic announcement days displays no pattern with the realized returns on those days. For example the FOMC announcements, which have the second highest realized returns, have the same realized volatility as the announcement days of the Monthly Budget Statement, which has the second lowest realized returns of -7.7% of the equity premium. In short the realized volatility is virtually identical across all 21 macroeconomic announcement series considered. This similarity in risk supports considering these announcement series together as ex-ante identical for identifying the expected return investors demand on macroeconomic announcement days.

That the risk is similar across all these announcement series but some have high ex-post returns and others have negative ex-post returns shows the excess Sharpe ratio puzzle documented by the literature. Considering only small sets of macroeconomic variables with high ex-post returns naturally leads to higher Sharpe ratios than investors expected ex-ante.

As additional measures of importance and risk Table 9 also includes the average VIX from the day before the announcement (VIX is forward looking) and the average dollar weighted trading volume for all stocks on the NYSE. Just as with realized volatility these values look similar across all announcement series. For example VIX for the FOMC is 19.68 which is virtually the same as the 19.56 value for consumer credit announcements which have the lowest realized returns.

## 2.5 Returns on Small Sets of Macroeconomic Announcement Days

Out of 21 macroeconomic announcement series, 13 account for more than 10% of the equity premium on their own. Individually, these positive average returns are less problematic than the negative returns. However, combined these 13 account for well over 100% of the equity premium, presenting a complementary puzzle to the negative returns just discussed. If these macroeconomic variables account for more than 100% of the equity premium in expectation, then other days must have negative expected returns.

One may worry that this ability to achieve more than 100% of the equity premium is due merely to an overlap in announcement days and hence a possible double counting of high return days. In this section we show that not to be the case. We also show this this too much return puzzle is robust to not only our sample but also many sets of macroeconomic announcements.

The literature has looked at small sets of macroeconomic announcement to test the joint hypothesis that expected returns should be earned when risk is expected to be resolved and that macroeconomic announcements are a source of such expected risk resolution. The ostensible reason for focusing on small sets of announcements is the reasonable goal of narrowing announcements to the most important ones. The problem is that it is not clear ex-ante which of these macroeconomic series are most important.

Theory seems to provide guidance on how to identify them: the most important announcements are those accompanied by the highest expected returns. However as Table 9 suggests, using realized returns as a proxy for expected returns can be problematic. Realized returns can diverge substantially from expected returns leading to concentrations of more than a 100% of the equity premium or implausible negative estimates of expected returns.

## 2.6 Similarity to Prior Samples

The too-much-return findings of Table 9 are not due to an oddity of the sample period we select. This problem of too-much-return is apparent as soon as one jointly considers the finding of Cieslak et al. (2019) that "the equity premium is earned entirely in weeks zero, two, four and six in FOMC cycle time" with the finding of Savor and Wilson (2013) that "60% of the cumulative annual equity risk premium is earned on announcement days" of inflation, unemployment and FOMC. One way of reconciling these would be to show that Savor and Wilson (2013) is due entirely to the FOMC. Table 9 shows this is not the case. The FOMC announcement days accounts for 32% of the equity premium its own. We replicate the finding of Savor and Wilson (2013) finding the three announcements they consider account for 57% of the equity premium in our sample with 26.5% due to inflation and unemployment announcements (Appendix Table 18).

## 2.7 Robust to Other Sets of Macroeconomic Announcements

Having confirmed that our sample period is similar to those previously studied, Table 10 shows that the concentration of over 100% of the equity premium on a handful of macroeconomic announcement days is not due to the overlap in announcement days between variables and is not unique to the set of variables chosen by the prior literature. More precisely, Table 10 shows the concentration of the equity premium using sets of 1 to 5 macroeconomic variables.[16] Panel A shows these combinations including the FOMC. Panel B omits the FOMC to highlight that we are not simply finding a repeat of the FOMC explaining all of the equity premium.

Panel A shows the top 5 announcement series earn 125% of the equity premium and Panel B shows the top 5 excluding the FOMC earn 103% of the equity premium. That the unemployment rate, featured in Savor and Wilson (2013), only enters when we consider

[16]Days with two announcements are not counted twice and we create the exact distribution of (all) combinations of 1 through 5 macroeconomic variables chosen from the full set of 21.

**Table 10**
**Combinations of Macroeconomic Announcements with Largest Concentration of the Equity Premium** This table reports the top combinations of 1 through 5 macroeconomic announcements that jointly achieve the highest percent of the cumulative annual equity premium. Panel A includes the FOMC, and Panel B excludes the FOMC.

Panel A: With FOMC

| Announcement 1 | Announcement 2 | Announcement 3 | Announcement 4 | Announcement 5 | % of EP |
|---:|---:|---:|---:|---:|---:|
| Const Spend | | | | | 36.2% |
| Const Spend | FOMC | | | | 69.2% |
| Const Spend | Consumer Conf | FOMC | | | 89.1% |
| Const Spend | Consumer Conf | New Home Sales | FOMC | | 106.2% |
| Unemploy Rate | Const Spend | Consumer Conf | New Home Sales | FOMC | 124.2% |

Panel B: Without FOMC

| Announcement 1 | Announcement 2 | Announcement 3 | Announcement 4 | Announcement 5 | % of EP |
|---:|---:|---:|---:|---:|---:|
| Const Spend | | | | | 36.2% |
| Const Spend | Consumer Conf | | | | 55.4% |
| Housing Starts | Const Spend | Consumer Conf | | | 71.3% |
| Unemploy Rate | Const Spend | Consumer Conf | New Home Sales | | 86.3% |
| Unemploy Rate | Housing Starts | Const Spend | Consumer Conf | New Home Sales | 102.5% |

combinations of 5 or more announcements shows that one could have picked many other combinations of two or three variables and found similar or stronger results. Consumer confidence and real-estate related variables seem just as "important" ex-post, and one could plausibly argue these are ex-ante just as important as unemployment and inflation given the role consumption and housing play in the economy.

That one can earn about 125% of the equity premium by holding the market on FOMC, consumer confidence, construction spending, unemployment, and new home sales announcement days means that 56 days per year generate 125% of the equity premium. If this represents the true expected return, it implies that there is a predictably large negative expected return earned on all other days. While the FOMC is important, Panel B shows that one can generate similarly puzzling results without it.

Beyond these top few combinations, many other combinations of macroeconomic announcements generate large concentrations of the equity premium. We see this in Figure 4 which shows the histogram of the fraction of the equity premium earned on all combinations of two and three macroeconomic announcement series. For the combination of two series we omit the FOMC to show the results are not driven solely by that announcement. Summary

**Table 11**

**Summary Statistics of Distributions of Equity Premium Concentration** This table presents summary statistics for the distributions of combinations of all sets of macroeconomic announcements. The first column shows the values for combinations of two announcements and the second column shows combinations of three announcements. These accompany the distributions shown in Figure 4.

| | Two Announcements | Three Announcements |
|---|---|---|
| Mean | 19.4% | 31.4% |
| Standard deviation | 14.5% | 18.1% |
| 25th percentile | 8.0% | 17.9% |
| Median | 18.9% | 30.8% |
| 75th percentile | 28.3% | 43.3% |
| 95th percentile | 45.5% | 61.7% |

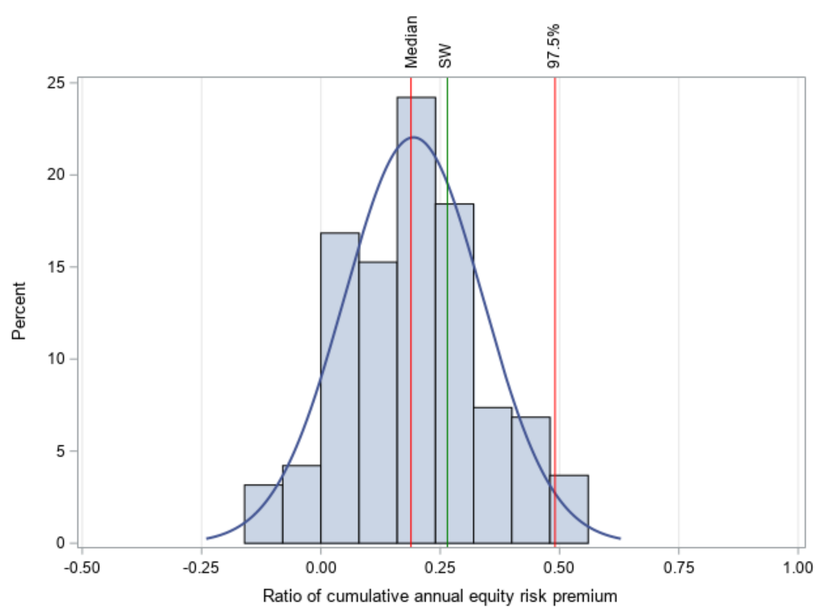
statistics of these distributions are in Table 11. The median equity premium for a set of two announcements is 19% and for three announcements is 31%. The concentration for the 95th percentile combinations of announcements is 45.5% and 62% respectively. Thus we see many combinations of announcements produce large concentrations of the equity premium.

These distributions help put the prior literature's finding of the concentration of the equity premium in the unemployment, inflation and monetary policy announcements in a broader perspective. The prior literature (e.g., Savor and Wilson (2013)) finds that this concentration of the equity premium is statistically significantly different from on *non-announcement days*. We replicated this finding in Appendix Table 18.

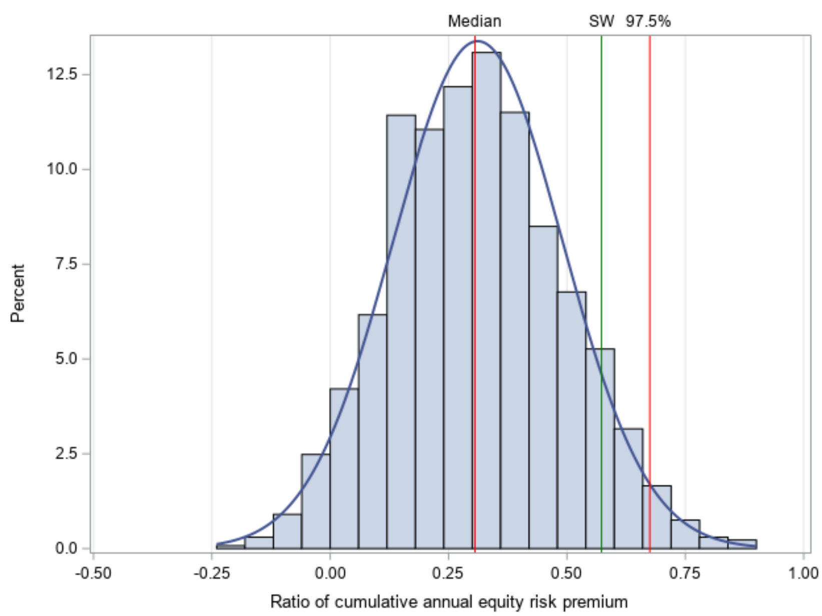
With the distributions of all combinations of 2 or 3 macroeconomic announcements we can ask a different question: is the concentration of the equity premium on the combination of inflation and unemployment announcement days or the combination of inflation, unemployment and monetary policy announcement days statistically different from other macroeconomic announcement days? We see that they are not.

The green lines on Figure 4 shows where the combination of unemployment, inflation and the FOMC fall in these distributions. The combination of unemployment and inflation announcements considered by Savor and Wilson (2013), which has 26.5% of the equity premium, falls in middle of the distribution (70th percentile) of all possible combinations of macroeconomic variables. Including the FOMC as well in Panel B raises the concentra-

**Fig. 4. Distributions of the Percentage of the Equity Premium for all Combinations of Two or Three Macroeconomic Variables** This figure shows histograms of the concentration of equity premium earned for every combination of two or three macroeconomic variables. Panel A is the distribution from selecting 2 variables, excluding the FOMC. Panel B is the distribution from selecting 3 variables, including the FOMC. The x-axis shows the percentage of the equity premium earned. The y-axis show the frequency. The solid line is a normal distribution best fit. The green line shows the value for the combination of announcement series considered by Savor and Wilson (2013) with and without the FOMC. The red lines show the median and 97.5th percentile values.




Panel A: Two macroeconomic variables, excluding FOMC




Panel B: Three macroeconomic variables, including FOMC

tion to 57.3% but this combination still only falls at the 91st percentile. (Table 9 shows that even the FOMC announcement alone is not statistically significantly different from all other macroeconomic announcements falling only at the 95% short of the 97.5% threshold for standard significance.)

The fact that these are relatively "ordinary" macroeconomic variables suggests that the existing literature did not report the variables with the highest ex-post concentration of the equity premium, i.e., not directly data mine. Further their similarity to other macroeconomic announcement series does not support separating them out as special for consideration alone. Thus we argue that the ex-ante similarity of the 21 monthly macroeconomic announcement series makes considering them together a better measure of the economic importance of macroeconomic announcements.

Finally, the fact that combining announcement series other than those chosen by the literature produces even stronger concentrations makes the too-much-return puzzle even more puzzling. Similarly these more extreme combinations, exacerbate the excess Sharpe ratio puzzle since we have documented in Table 9 that all the announcement series have similar risk.[17]

## 2.8 Macroeconomic Announcements are Clustered

Comparing Table 9 of the individual announcements with the highest concentration of the equity premium to the sets of announcements with the highest concentration in Table 10 shows that the top individual announcements do not always make it into the top set. The absences are due to overlap in macroeconomic announcements in time. The announcements cluster in time in part because agencies responsible for the announcements have a set announcement pattern. For example the unemployment rate is almost always released at the beginning of the month, with the mode on the fifth trading day. This is consistent with the

[17] The literature including Savor and Wilson (2013) has shown that the Sharpe ratio on macroeconomic announcement days is as much as an order of magnitude larger than the Sharpe ratio on non-announcement days.

Bureau of Labor Statistics' rule of announcing on the first Friday of each month.

Table 12 reports, for each macroeconomic variable, the number of times an announcement is made on the first trading day of the month (day 1), the second trading day of the month (day 2), ..., the last trading day of the month (day -1). Since the minimum number of trading days per month in our sample is 18 and the maximum is 23, we group the "middle" days together (up to five of them).[18] This grouping allows us to always identify the beginning and ending days of the month separately from each other and follow the number in Etula et al. (2019)

Table 12 shows the clustering of macroecononomic announcements at the beginning, middle and end of the month. Announcments tend to cluster around months ends because the announcement rules tend to reference month ends: like the first day of the month, the first Friday of the month, or the third Tuesday of the month, etc. Unsurprisingly announcements that cluster in time tend to have similar returns. For example the announcements with the highest concentration of the equity premium from Table 9 are concentrated at the beginning of the month.

This clustering makes drawing inferences about the the relative importance of macroeconomic announcements from their individual average returns difficult. Further because macroeconomic announcements tend to cluster at times, such as months' ends, when other factors are know to be important, the average announcement returns can be misleading. Months' ends are high information times beyond macroeconomic annoucements due to firms closing monthly books and this information entering markets into market. Further months' ends are periods of higher capital in and outflows that drive market returns due to slow moving capital (Duffie, 2010). Etula et al. (2019) in particular shows institutional needs for cash, e.g., pension funds, drive higher returns at these end of month times. (Also see Ogden (1990); Meng and Pantzalis (2018) and references therein for the large literature on these seasonal effects.)

[18] September 2001 is the one exception with even fewer trading days.

Given the question of interest is how much information and risk (and hence expect returns) are due the information flow from macroeconomic announcements, it is important to separate out the effects of other information flow, capital flows and other seasonal contaminates from the returns due to macroeconomic announcements. Table 12 shows that though some announcements are concentrated at specific points in the month there is variation in the timing of the announcments. Further we see there is variation in most individual announcements across several days due to such effects at the first Friday of the month falling a different number trading days into each month. In the next section, we exploit not only the variation across annoucements, but also the variation of timing within announcments to separate these effects.

**Table 12**

**Timing of Macroeconomic Announcements** This table records the number of times each macroeconomic variable is released on a given trading day of the month. Days 1 through 9 are the first nine trading days of the month. Days -1 through -9 are the last nine trading days of the month. Mid are the remaining middle days of the month (zero to five days with an average of three days).

| | Trading Day | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Mid | -9 | -8 | -7 | -6 | -5 | -4 | -3 | -2 | -1 |
| Const Spend | 303 | 24 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 9 |
| FOMC | 8 | 12 | 13 | 8 | 5 | 2 | 9 | 8 | 7 | 37 | 17 | 25 | 8 | 6 | 5 | 13 | 19 | 12 | 14 |
| NAPM | 338 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Consumer Conf | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 36 | 128 | 62 | 49 | 46 |
| New Home Sales | 3 | 39 | 6 | 3 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 6 | 35 | 60 | 49 | 48 | 51 | 37 |
| Housing Starts | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 163 | 91 | 63 | 18 | 1 | 1 | 0 | 2 | 0 | 0 |
| Unemploy Rate | 23 | 43 | 45 | 72 | 117 | 21 | 9 | 3 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| UM Cons Conf F | 30 | 16 | 6 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 23 | 18 | 26 | 37 | 44 | 120 |
| PPI | 1 | 0 | 0 | 0 | 1 | 7 | 26 | 43 | 78 | 141 | 15 | 13 | 9 | 2 | 0 | 1 | 2 | 0 | 1 |
| Adv Retail Sales | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 204 | 122 | 3 | 1 | 1 | 0 | 0 | 0 | 2 | 1 | 0 |
| Durable Goods | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 51 | 75 | 66 | 103 | 40 | 2 |
| Personal Consumpt | 79 | 15 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 20 | 11 | 12 | 30 | 56 | 110 |
| Capacity Util | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 | 298 | 21 | 8 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| Factory Orders | 5 | 132 | 104 | 55 | 7 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 34 |
| CPI | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 14 | 31 | 216 | 28 | 18 | 11 | 13 | 2 | 2 | 0 | 3 | 0 |
| Trade Balance | 0 | 8 | 23 | 21 | 12 | 8 | 23 | 53 | 21 | 65 | 42 | 35 | 21 | 7 | 0 | 0 | 0 | 1 | 1 |
| Business Inventory | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 3 | 87 | 237 | 7 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| Lead Indicators | 29 | 50 | 14 | 3 | 1 | 0 | 0 | 0 | 0 | 39 | 32 | 43 | 62 | 27 | 5 | 2 | 5 | 11 | 18 |
| UM Cons Conf P | 0 | 0 | 0 | 0 | 4 | 5 | 9 | 14 | 48 | 211 | 23 | 7 | 5 | 1 | 0 | 0 | 0 | 0 | 0 |
| Mthly Budget Stmnt | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 143 | 13 | 15 | 18 | 47 | 38 | 30 | 19 | 4 | 3 | 0 | 0 |
| Consumer Credit | 0 | 0 | 0 | 5 | 326 | 6 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Any Announcement | 822 | 340 | 214 | 172 | 473 | 52 | 83 | 288 | 498 | 1546 | 299 | 262 | 189 | 218 | 232 | 304 | 313 | 272 | 393 |

## 2.9 Fixed Effects Regressions

The key prediction of this literature is that expected returns should be earned when news is expected to be announced. As scheduled news events, macroeconomic announcements should create higher expected returns on those scheduled news announcements. When a schedule announcement day changes in a known way each month the expected return should move each month to that scheduled day. We exploit this prediction as our identifying assumption in fixed effect regressions to separate the news and expected return effects due to macroeconomic announcements from other seasonal information and capital flows that affect market returns. We include fixed effects for the day-of-the-month to capture this variation in seasonal returns.

Across three specification we exploit three different sources of variation in the timing of macroeconomic announcements. Across all specification we obtain similar results. We begin the analysis treating all macroeconomic announcements the same ex-ante. We then allow for the series to each have their own average return to show what can be learned from the differences in returns across these series.

## 2.10 Considering Announcement Series Jointly

In our main specification we consider all macroeconomic announcements the same ex-ante using a single binary fixed effect that is 1 if any macroeconomic announcement takes place and zero otherwise. This fixed effect exploits the variation in different announcement series taking place at different times of the month but allowing them to have the same average information content. We include a baseline specification that ignores seasonalities by treating all days the same.

Our main results of interest include a fixed effect for the day-of-the-month, to control for the known fact that different trading days of the month have different average return. We continue our numbering of the days-of-the-month as in previous section that allows us to clearly identify the beginning and end of month effects. Our results are robust to alternative numberings.

To ease interpretation of the regression estimates, we scale the daily excess market returns by the average daily market return (7.97%/252 over our sample period). Hence the regression coefficients can be interpreted as the percent of the daily average equity risk premium attributable to the macroeconomic announcement (per announcement). Therefore, a coefficient of zero indicates that the macroeconomic announcement contributes no additional equity premium. A coefficient of one indicates that the macroeconomic announcement earns 100% more of the average *daily* equity risk premium.

Table 13 shows the results of the following regression equations

$$r^e_{m,t} = \phi_{\text{all}} \mathbb{1}(Macro_{\text{all}}) + \varepsilon_t \quad \text{and} \tag{10}$$

$$r^e_{m,t} = \phi_{\text{all}} \mathbb{1}(Macro_{\text{all}}) + \sum_{j=-9}^{9} \gamma_j \mathbb{1}(Tradeday_j) + \varepsilon_t. \tag{11}$$

Panel A shows the fixed effect for the single macroeconomic announcement across the two specifications. We see that without the day-of-the-month fixed effects, the macroeconomic fixed effect is large, economically and statistically significant. In the presence of the day-of-month fixed effects, it is much smaller and no longer statistically significant.

Panel B shows the day-of-month fixed effects. They have large values where the macroeconomic announcements are concentrated: first and last days of the month along with the very middle days. In contrast to the statistical insignificant macroeconomic announcement fixed effect, the day-of-the-month fixed effects are jointly significant (F-test P-value of 0.0498). This statistically significance confirms that they are not operating by simply inducing noise. The average day-of-month fixed effect is 0.42. Which contrasts with the negative intercept when we do not allow for the variation in the average daily returns.

After controlling for the day-of-month fixed effects, the concentration of the equity premium across all 21 macroeconomic series can be computed in two ways. An arithmetic upper bound, which does not account for volatility and a geometric lower bound which allow for volatility. It is a lower bound because we cannot fully separate any day's particular volatil-

**Table 13**

**Single Macroeconomic Announcement Fixed Effect** This table records the coefficient estimates from the fixed effects regressions with a single fixed effect that is equal to 1 if there is any macroeconomic announcement on a given day. This is consistent with treating all macroeconomic announcements the same ex-ante. The baseline specification is:

$$r^e_{m,t} = \alpha + \phi_{all}\mathbb{1}(Macro_{all}) + \varepsilon_t$$

and the full specification is:

$$r^e_{m,t} = \phi_{all}\mathbb{1}(Macro_{all}) + \sum_{j=-9}^{9}\gamma_j\mathbb{1}(Tradeday_j) + \varepsilon_t.$$

Panel A shows the fixed effect of the macroeconomic announcements for both specifications along with the intercept for the first specification. Panel B shows the day-of-month fixed effects. It also shows the average day-of-month fixed effect where the Mid fixed effect is counted 3 times consistent with its average appearance (for an average of 21 days per month). For ease of interpretation daily returns are divided by the average daily equity premium. Standard errors are in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent levels. The test of joint significance (F-test) for the day-of-month fixed effects gives a P-value of 0.0498.

Panel A: Fixed effect on the macroeconomic announcements

| | Day of the month fixed effects | |
|---|---|---|
| | Excluded | Included |
| $\phi_{all}$ | 2.01** | 0.94 |
| | (0.84) | (0.92) |
| $\alpha$ | -0.24 | |
| | (0.65) | |

Panel B: Fixed effects on the days of the month

| Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ |
|---|---|---|---|---|---|
| 1 | 4.69** | 8 | -0.86 | -6 | -2.57 |
| | (2.08) | | (1.95) | | (1.90) |
| 2 | 1.36 | 9 | 3.11 | -5 | -1.62 |
| | (1.97) | | (2.00) | | (1.92) |
| 3 | 0.12 | Mid | 1.88 | -4 | 4.03** |
| | (1.92) | | (1.30) | | (1.95) |
| 4 | -0.21 | -9 | -0.48 | -3 | 2.47 |
| | (1.90) | | (1.95) | | (1.97) |
| 5 | -2.32 | -8 | -1.01 | -2 | 2.38 |
| | (2.06) | | (1.95) | | (1.94) |
| 6 | -1.22 | -7 | -4.54** | -1 | 1.12 |
| | (1.86) | | (1.91) | | (1.99) |
| 7 | -1.25 | | | | |
| | (1.88) | | | | |
| Average FE | 0.42 | | | | |
| | (NA) | | | | |

ity between that due to the macroeconomic announcement and other news or capital flows. The arithmetic measure comes from multiplying the fixed effect by the 61.6% of days which include a macroeconomic announcement. This gives 57.9% (= 0.94 × 61.6%) being due to macroeconomic announcements. Thus though this point estimate is statistically insignificant it is economically significant.

The geometric method relies on the statistically significant day-of-month fixed effects. Using them we construct an alternative times series for the announcement days by subtracting off the daily average returns captured by these fixed effect. With this new series we compute geometric return concentrations as in Table 9. This geometric calculation gives 56.1% of the equity premium due to the macroeconomic announcements.

Though this total is near the 60% reported in Savor and Wilson (2013) for their subset of three macroeconomic announcements, the interpretation is importantly different. Their value is obtained on only 13% of trading days. Our same total is earned over nearly five times as many days (62%). Our total is the same despite the larger number days because there are many macro announcements with higher ex-post returns than those selected by Savor and Wilson and many macro announcement with lower ex-post returns (see Table 11 and Figure 4).

That the premium for macroeconomic risk is earned over vastly more days is important for understanding the risk return trade-off for risk resolved from macroeconomic announcements. Focusing on only a small set of days led to the puzzle of seemingly insufficient risk on those days to explain the higher returns. This is the puzzle of excessively high Sharpe ratios–an order of magnitude larger–on this small subset of macroeconomic announcements days considered by Savor and Wilson compared to non-announcement days. When the premium is earned over nearly five times as many days, the small increase in risk on those days is able to explain the higher premium.

**Robust to non-binary fixed effect**

The binary fixed effect for whether an announcement is present or not is consistent with how the prior literature treated announcements for the smaller sets they used (Savor and Wilson, 2013). Further as simulations in the next section show, this binary fixed effect can reliably recover the equity premium concentration. Nevertheless, for robustness, we consider a non-binary fixed effect that counts the number of macroeconomic announcmennts on a given day and is zero if none take place. This allows for multiple announcements on a given day to have a larger information effect and a correspondingly larger expected return. This non-binary fixed effect exploits the variation in that days may different numbers of announcements, while still treating all the macroeconomic annoucement the same ex-ante.

Appendix Table 13 presents the results for this specification with and without day-of-month fixed effects. We obtain similar results to the binary fixed effect specification. After controlling for the day-of-month fixed effects the macroeconomic announcement fixed effect gives 46.1% of the equity premium is due to the 21 macroeconomic announcements. These announcements are still spread across 62% of actual days. However to interpret the fixed effect one must consider multiple announcements on a day, mean if spread out to individual days the announcements would cover 98% of the total days. Thus to convert the fixed effect coefficient 0.47 to the equity premium concentration, one must multiply by 0.98. ($46.1\% = 0.98 \times 0.47$.)

## 2.11 Fixed Effects for Individual Announcement Series

Though we argue that the macroeconomic announcement series should be considered ex-ante identical, we can allow for a separate fixed effect for each macroeconomic series. This alternative allows us to consider the ex-post average of these series separately while still controlling for day-of-month return variation and overlap in announcements. In essence this is the same as the non-binary fixed effect, except we do not restrict each announcement to have the same expected return. This specification has the disadvantage of introducing more noise from ex-post surprises because we are not averaging these surprises across the entire set of macroeconomic announcements.

These fixed effects rely on the variation within the timing of individual macroeconomic announcement series for identification rather than the larger variation in timing across announcement series. For the majority of announcements this is not a problem. For example the announcement of consumer confidence typically falls four days before the end of the month. It also often falls on any of the five days prior to the end of the month. The prediction is that if the concentration in the equity premium is due to the expected information content of the consumer confidence report, then this higher expected return should occur on the announcement day as it varies with respect to the end of the month. If however, part of the equity premium concentration is due to the general information released throughout the economy on days near the end of the month, then that concentration should not vary as the timing of the consumer confidence announcement varies.

Table 14 shows the results for the following regressions without and with day-of-month fixed effects:

$$r^e_{m,t} = \alpha + \sum_{i=1}^{21} \phi_i \mathbb{1}(Macro_i)_t + \varepsilon_t \quad \text{and} \tag{12}$$

$$r^e_{m,t} = \sum_{j=-9}^{9} \gamma_j \mathbb{1}(Tradeday_j) + \sum_{i=1}^{21} \phi_i \mathbb{1}(Macro_i) + \varepsilon_t. \tag{13}$$

Panel A shows the fixed effect coefficients for the announcement series with and without the day-of-month fixed effects. We see that there is wide variation across these fixed for the series. This variation is consistent with the variation seen in the tabulation of the equity premium concentration in Table 9. Once the day-of-month fixed effects are included only the FOMC announcements are statistically significant. However, one must take the multiple comparison problem seriously as there are 21 series considered. The F-test for joint significance of these series fixed effects is 1.16 with a P-value of 0.28. Thus the FOMC significance is just as one would expect if it were ex-ante identical to the other macroeconomic

**Table 14**
**Fixed Effects for Individual Macroeconomic Announcements** This table records the coefficient estimates from a regression with a separate fixed effects for each macroeconomic announcement. One regression includes only announcement fixed effects:

$$r^e_{m,t} = \alpha + \sum_{i=1}^{21} \phi_i \mathbb{1}(Macro_i)_t + \varepsilon_t.$$

The other regression also includes day-of-month fixed effects:

$$r^e_{m,t} = \sum_{j=-9}^{9} \gamma_j \mathbb{1}(Tradeday_j) + \sum_{i=1}^{21} \phi_i \mathbb{1}(Macro_i) + \varepsilon_t.$$

Panel A lists the coefficients on the macroeconomic variables. Panel B lists the coefficients on the days of the month. Panel B also includes the average day-of-month fixed effect where the mid fixed effect is include 3 times for its average number of times (21 days in the average month). For ease of interpretation, daily excess market returns are scaled by the cumulative annual equity premium divided by 252 trading days. Standard errors are in parentheses. *, **, and *** indicate significance at the 10, 5 and 1 percent levels. For the regression without day-of-month fixed effects, the F-statistic for the joint significance of the macro announcement fixed effects in the combined regression is 1.67 with a P-value of 0.0276. For the regression with day-of-month fixed effects, the F-statistic for the joint significance of the macro announcement fixed effect is 1.16 with a P-value of 0.2804. The F-statistic for the joint significance of the day-of-the-month fixed effects is 1.26 with a P-value of 0.1963.

Panel A: Fixed effects on the macroeconomic variables

| | Without DOM FE | With DOM FE | | Without DOM FE | With DOM FE |
|---|---|---|---|---|---|
| Unemployment Rate | 2.92 | 3.42 | Consumer Conf | 2.96 | 0.90 |
| | (2.06) | (2.13) | | (2.00) | (2.23) |
| CPI | 0.29 | -0.54 | Factory Orders | 0.65 | 0.54 |
| | (2.05) | (2.09) | | (1.95) | (2.22) |
| Durable Goods | 1.07 | 0.54 | NAPM | -2.22 | -12.90 |
| | (2.00) | (2.15) | | (4.01) | (13.10) |
| Housing Starts | 2.18 | 1.84 | New Home Sales | 2.00 | 1.75 |
| | (2.00) | (2.13) | | (2.01) | (2.05) |
| Lead Indicators | -0.86 | -0.21 | Personal Consumpt | -0.19 | -0.75 |
| | (1.94) | (2.00) | | (2.10) | (2.17) |
| Trade Balance | 1.26 | 1.19 | Mthly Budget Stmnt | -1.92 | -0.61 |
| | (1.96) | (1.99) | | (1.97) | (2.16) |
| PPI | 1.88 | 1.39 | Consumer Credit | -2.26 | 1.64 |
| | (2.05) | (2.08) | | (2.05) | (6.50) |
| Adv Retail Sales | 2.82 | -0.01 | Umich Cons Conf P | -2.32 | -3.23 |
| | (2.24) | (2.64) | | (2.11) | (2.14) |
| Capacity Util | 1.84 | -0.03 | Umich Cons Conf F | 1.57 | 0.79 |
| | (2.11) | (2.24) | | (2.10) | (2.21) |
| Business Inventory | -1.55 | -2.78 | FOMC | 7.50*** | 7.25*** |
| | (2.24) | (2.32) | | (2.33) | (2.34) |
| Const Spend | 8.20** | 7.30 | | | |
| | (4.02) | (4.17) | | | |

**Table 14**
**Continued...**

Panel B: Fixed effects on the days of the month.

| Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ |
|---|---|---|---|---|---|
| 1 | 11.59 | 8 | -0.44 | -6 | -2.48 |
| | (13.36) | | (2.11) | | (1.92) |
| 2 | 0.46 | 9 | 4.53* | -5 | -1.75 |
| | (2.15) | | (2.41) | | (1.97) |
| 3 | -0.42 | Mid | 3.24** | -4 | 3.64* |
| | (2.00) | | (1.50) | | (2.12) |
| 4 | -0.89 | -9 | -0.61 | -3 | 2.12 |
| | (1.95) | | (2.00) | | (2.05) |
| 5 | -4.27 | -8 | -1.31 | -2 | 2.25 |
| | (6.50) | | (1.97) | | (1.98) |
| 6 | -1.41 | -7 | -4.34** | -1 | 0.96 |
| | (1.87) | | (1.93) | | (2.16) |
| 7 | -1.43 | | | | |
| | (1.88) | | | | |
| Average FE | 0.29 | | | | |
| | (NA) | | | | |

announcements. We explore this issue more in the next section via simulations.

Panel B shows the day-of-month fixed effects. The average value of these is 0.29 which is similar to the 0.42 value when the macroeconomic series are considered jointly. These fixed effects are jointly statistically insignificant with an F-test P-value of 0.20. Nevertheless they are closer to significance than the individual macroeconomic announcement series. This lack of significance across both sets of fixed effects is consistent with our argument that there is insufficient information in the data to separately identify the expected returns of the individual macroeconomic announcement series.

### Overall equity premium concentration lower

Setting aside the statistical significance the economic significance of the equity premium attributable the announcement series somewhat lower, to that when the series are considered jointly. In Appendix Table 20 we repeat the arithmetic and geometric equity premium concentrations used in the previous subsection. We accumulate these concentrations in the order of the largest announecment fixed effects from the specification without the day-of-month fixed effects.

Accumulating the equity premium announcement by announcement lets us see another way that using small sets of ex-post identified important announcement series still leads to the too much return problem of over 100% of the equity premium. However including all the macroeconomic series elminates this issue. Considering the announcement series separately attributes 24% and 13% of the equity premium to the macroeconomic announcments by the arithmetic and geometric methods.

**Robust to excluding announcements with limited variation in timing**

Separating returns into the seasonal component and that due to macroeconomic announcements relies on there being sufficient variation in the timing of macroeconomic announcements. When considered jointly and ex-ante the same, there is sufficient variation.[19] One may nevertheless worry about that variation after reviewing the announcement timings in Table 12 and finding three macroeconomic announcements have very little variation in their announcement day pattern. The NAPM index, for instance, is always released on the first day of the month, with only 3 exceptions over our entire sample period. Consumer credit and construction spending also have little variation in their announcement patterns.[20] This limited variation manifests as excess noise in the fixed effect estimates for these series when considered individually. This noise is seen in both the large standard errors and large differences in those series fixed effects compared to the case where the day-of-month fixed effects are omitted.

We omit these three announcment series to show that their limited variation does not drive our results. Appendix Table 21 reports the results of the regressions with a single binary fixed effect for all the macroeconomic announcement series with and without day-of-month fixed effects omitting those three series. The average day-of-month fixed effect is 0.36 versus

[19]Recall that when considered jointly the identification comes from variation across all announcement series, which all fall throughout the month.

[20]This small variation leads to additional noise, hence higher standard errors, in the fixed effect point estimates for the separate fixed effects. It has no such effect on joint fixed effect for all announcements.

0.42 when those series are included. The day-of-month fixed effects are statistically significant at the 5% level. This specification attributes 63.9% (=55.6% of days with announcements times the coefficient 1.15) of the equity premium to macroeconomic announcements, which is similar to the 57.9% arithmetic measure from the main specification. The geometric average based fraction of the equity premium after accounting for the day-of-month effects is 59%.

## 2.12 Simulations

The underlying question of using a large set of macroeconomic announcements to average out the ex-post surprises, is what if only some of these macroeconomic announcements are truly important? By truly important we mean that an announcement reveals expected news to the market and hence earns an expected return. In this section we build a simulation to show four things. (1) The observed data is insufficient to identify important subsets of macroeconomic announcements from their realized returns. (2) A regression with a fixed effect that is 1 if any of the announcements from the large set occur and zero otherwise can reliably identify the amount of the equity premium earned by all the important announcements. (3) The fixed effect regression accomplishes this even if the large set contains some extraneous announcements. (4) In contrast a fixed effect regressions using only subsets of macroeconomic announcement identified as important from realized returns does not recover the actual concentration of equity premium earned by all the truly important macroeconomic announcements.

## 2.13 Simulation Methodology

We draw a series of daily returns of the same length as our sample period, simplifying to all months having 21 trading days for 252 trading days in a year. We have a set of 21 monthly macroeconomic announcements. For each simulation run we randomly assign each announcement to an anchor trading day of the month via a uniform distribution. For each month we allow each announcement to vary in its actual announcement date from two days before to two days after this anchor date. Again we use a uniform distribution. This announcement timing captures that many macroeconomic announcement rules lead to planned variation around a particular trading day of the month, e.g., first Friday of the month. We truncate this variation at the beginning and end of each month to assure that each month has one of each announcement series. This truncation creates a clustering at the beginning and end of the month as in the actual data.

Of the 21 announcements we randomly choose $M$ to be important for each simulation run. Being important means that news is released and an expected return is earned in proportion to the variance of that expected news. All important announcement days are equal in the amount of expected news. In total the important announcements earn fraction $f$ of the equity premium and fraction $f$ of the market variance. Where there total equity premium, $\mu_m$, and market variance, $\sigma_m^2$, are calibrated to match the data. This means each important announcement contributes a normal return shock on its announcement day with mean $f\left(\frac{\mu_m}{252M}\right)$ and variance $f\left(\frac{\sigma_m^2}{252M}\right)$. These shocks are cumulative across important announcements, so if multiple important announcements occur on a day, multiple independent shocks occur. Unimportant announcements have no return sock or expected return associated with them.

The remaining $1-f$ of the equity premium and market variance is earned evenly over all days. Each day regardless of announcements also has a normally distributed return shock with mean $(1-f)\frac{\mu_m}{252}$ and variance $(1-f)\frac{\sigma_m^2}{252}$. The daily shocks combined with the announcement shocks aggregate to the total equity premium and market variance.

We run the simulation 10,000 times for each calibration. We consider calibrations where 30%, 60% and 80% of the equity premium are earned by the important macroeconomic announcements. We consider cases of 1, 3, 5, 7, 10, 15 and 21 important announcement series.

## 2.14 Data Is Insufficient to Identify Number of Important Announcements

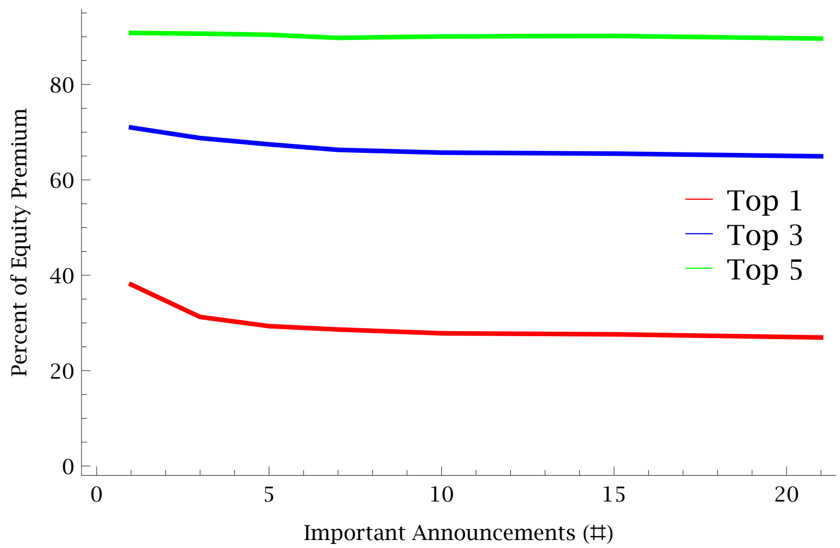
Using the calibration close to the data where 60% of the equity premium is attributable to all important macroeconomic announcements, we ask the following questions. (1) Is the high concentration of the equity premium as measured by realized returns among a few macroeconomic announcements such as the FOMC alone or the FOMC plus inflation and unemployment a good indication that they are special? (2) Do the realized returns from the macroeconomic series with the largest realized returns accurately capture the expected returns for that number of important announcement series? (3) Can the concentration of the equity premium in subsets of macroeconomic announcement series with the highest realized return identify the number of important announcements?

Figure 2 plots the median across all simulations of the percent of the equity premium earned by the subsets of 1, 3 or 5 macroeconomic announcement series (red, blue and green lines) with the highest realized returns within each simulation run. The x-axis shows the different number of important announcement series in each simulation.

We see that these lines do not vary strongly with the number of important announcements. That is we see high concentration in the few ex-post high return announcement series even when all 21 announcement series are equally important. Thus being included in this set does not indicate an announcement series is important or more important than those not included.

Further, we see these lines neither reliably reveal the 60% of the equity premium earned by the total set of important announcement series. Nor do they reveal the percent of the equity premium expected to be earned by a subset of that size. For example a subset of 1 important announcement series (red line) would be expected to have 2.9% of the equity premium when 21 announcements are important ($\frac{60\%}{21}$). Instead we see looking the red line, it is at 27%. Thus these subsets do not tell us much about the amount of the equity premium truly earned by macroeconomic announcements.

**Fig. 5. Simulation: Equity Premium in Top Ex-Post Announcement Series** This figure plots the median percent of the equity premium (geometric averages) for 10,000 simulation runs. The vertical axis shows the percent of the equity premium in a given subset. The red, blue and green lines show the percent accounted for by the subset of the ex-post highest 1, 3 or 5 macroeconomic announcement series for each simulation chosen out of a possible 21 macroeconomic series. The horizontal axis marks the number of important macroeconomic announcement series. The simulations are explicitly calculated for 1, 3, 5, 7, 10, 15, or 21 important macroeconomic announcement series. The plot interpolates linearly between them. The important macroeconomic announcement series are the only series to earn any additional equity premium. The equity premium for each of these series is $\frac{1}{N}$ of the total equity premium attributable to the macroeconomic announcements, where $N$ is the number of important series. These equity premium and variance are earned in proportion and split linearly across the important macroeconomic announcement series and all other days. The simulation is calibrated to assign 60% of the equity premium to the important macroeconomic announcement series. The total equity premium and market return variance is calibrated to match the actual data: 7.96% and 17.30% annualized.




Finally, one might hope that the concentration in these subsets would give insight into the number of important announcements. For example in the data the FOMC announcement series earns 32% of the equity premium. Perhaps this tells us that the FOMC is either truly different from the other announcement series or that only a few announcement series are important. Unfortunately this is not the case.

Table 15 show the median (Panel A) and 97.5 percentile (Panel B) simulation values for the percent of the equity premium earned by the subsets of the announcement series with the largest realized returns in each simulation for different numbers of important announcements. Panel A shows the values plotted in Figure 5.

**Table 15**
**Simulation Percentiles** This table records the 50 and 97.5 percentiles for the 10,000 simulation runs in Panels A and C. Values are the percent of the equity premium (geometric averages) accounted for by the subset of the ex-post highest 1, 2, 3, 4 or 5 macroeconomic announcement series for each simulation chosen out of a possible 21 macroeconoic series. Subset size varies across the rows. For each simulation there are either 1, 3, 5, 7, 10, 15, or 21 important macroeconomic announcment series. These vary across the columns. The important macroeconomic anouncement series are the only series to earn any additional equity premium. The equity premium for each of these series is $\frac{1}{N}$ of the total equity premium attributable to the macroeconomic announcements, where $N$ is the number of important series. These equity premium and variance are earned in proportion and split linearly across the important marcoeconomic announcment series and all other days. The simulation is calibrated to assign 60% of the equity premium to the important macroeconomic announcement series. The total equity premium and market return variance is calibrated to match the acutal data: 7.96% and 17.30% annualized.

Panel A: 50th Percentile

| | Number of Important Announcements | | | | | | |
|---|---|---|---|---|---|---|---|
| Subset Size | 1 | 3 | 5 | 7 | 10 | 15 | 21 |
| 1 | 38.1 | 31.3 | 29.3 | 28.6 | 27.8 | 27.6 | 27.0 |
| 2 | 56.7 | 52.7 | 50.8 | 49.7 | 48.9 | 48.6 | 48.0 |
| 3 | 71.0 | 68.8 | 67.5 | 66.3 | 65.7 | 65.5 | 64.9 |
| 4 | 82.1 | 81.2 | 80.3 | 79.4 | 79.3 | 79.2 | 78.6 |
| 5 | 90.8 | 90.7d | 90.4 | 89.8 | 90.1 | 90.2 | 89.6 |

Panel B: 97.5th Percentile

| | Number of Important Announcements | | | | | | |
|---|---|---|---|---|---|---|---|
| Subset Size | 1 | 3 | 5 | 7 | 10 | 15 | 21 |
| 1 | 157.4 | 149.3 | 161.3 | 134.7 | 134.0 | 143.9 | 156.6 |
| 2 | 243.3 | 243.5 | 276.1 | 228.9 | 232.9 | 250.2 | 270.3 |
| 3 | 302.0 | 308.5 | 356.2 | 296.3 | 305.5 | 329.5 | 349.0 |
| 4 | 347.2 | 363.6 | 410.0 | 346.0 | 353.5 | 388.5 | 410.6 |
| 5 | 387.6 | 401.5 | 452.8 | 389.6 | 397.1 | 432.4 | 458.4 |

We see that though there is variation in both panels across subset size and number of announcements there is large overlap in the distributions of concentrations. Thus the FOMC equity premium concentration of 32% is close to the median values for 1 important announcement series and 21 announcement series (top row of Panel A). Similarly the concentration of 57% of the equity premium in the FOMC, unemployment and inflation announcements is close to the median values for 1 to 21 important announcements (3rd row of Panel A).

Moving to a more formal hypothesis test at the 5% level, we can look at the 97.5% cutoffs from the simulations to see if these observed concentrations in the data are extreme enough to rule out any null of 1 to 21 important announcements. Looking at the top row of Panel B we see we cannot rule any of these out with the FOMC concentration. Moving to the third row of Panel B we see that with the combination of the FOMC, unemployment and inflation we cannot reject any of the nulls. This means looking at the concentration of a few ex-post high returning series provides little information about the number of important announcement series. Further these simulations provide evidence that the "large" concentrations of the equity premium observed in a few announcement series in the data are consistent with our maintained hypothesis of treating all 21 monthly macroeconomic announcement series as the same ex-ante.

**Concentrations more extreme when more potential announcements considered** The literature has not confined its search for the effects of macroeconomic announcement on returns to the announcement days themselves. The literature has considered many other permutations, including one or more days before the announcements, to even further before the announcements such as random days on various weekly or biweekly patterns. Such searches in effect increase the number of "possible" series considered without increasing the actual number of important announcements.

We show the effects of such extended searches within the simulation by increasing the number of considered announcement series to 42 while leaving the number of important series as before. This doubling is analogous to looking at a day before each series. We show in Appendix Table 22 the median and 97.5 percentiles across simulations of the equity premium concentrations. From these values we see with such a free search range, one obtains even higher equity premium concentrations. Adding even more possible days or combinations of days to the would make the results even more extreme. Thus it is not surprising the literature has found high concentration of the equity premium in some macroeconomic announcement series.

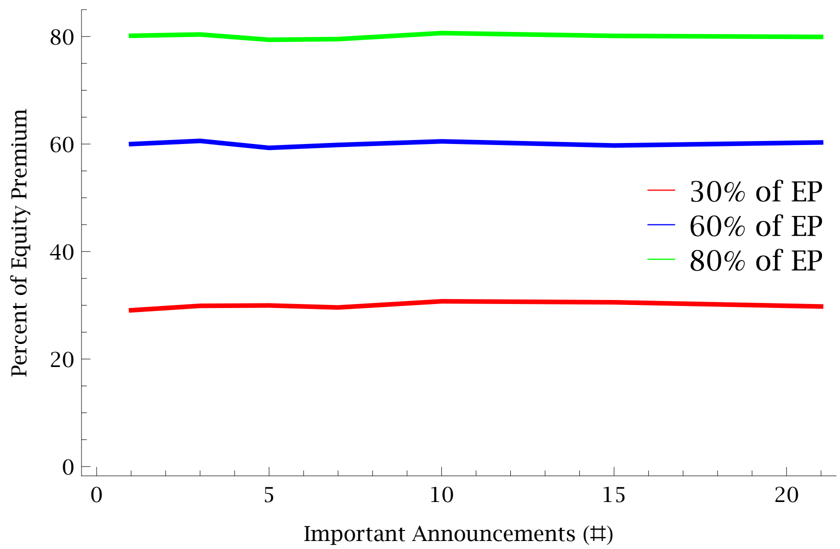
## 2.15 Even a Set Too Large Accurately Captures the Total Equity Premium Concentration

We argue that considering a large set of ex-ante similar announcement series helps by averaging out the noise of ex-post return surprises. One may worry about the effects of accidentally including too many unimportant announcement series. Specifically one worries if this causes a dilution of the equity premium concentration.

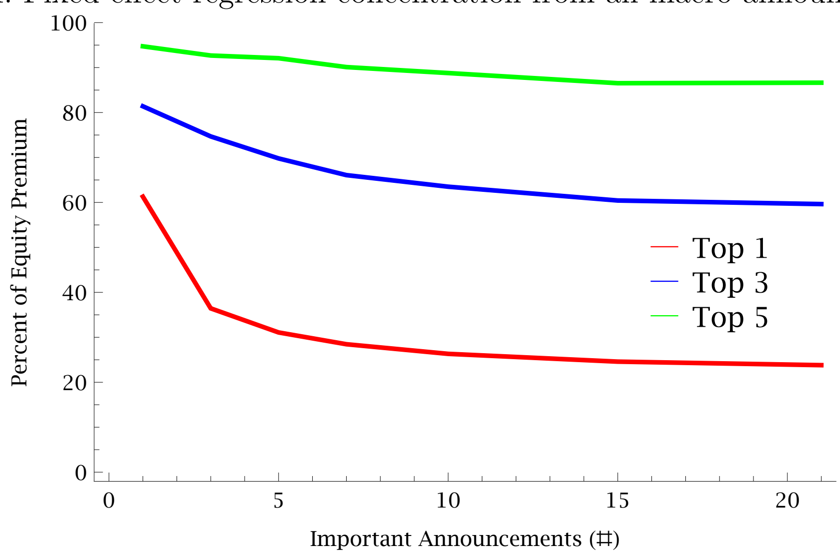
We address this in the simulation by running the same fixed effects regression as we did in the data. Since for simplicity we did not include seasonalities in the simulation data generating process, we do not need to include day-of-month fixed effects in these regressions. Panel A of Figure 6 plots the results analogous to our main specification (Table 13) of a single binary fixed effect with value 1 if an announcement from any of the 21 series occurs and zero otherwise. The figure plots the median concentration of the equity premium revealed by the coefficient from that regression. Specifically this is the coefficient times the fraction of observations where the fixed effect has value 1, i.e., fraction of announcement days.

We plot the results for three different calibrations of the equity premium attributable to the important macroeconomic announcements: 30% (red), 60% (blue) and 80% (green). The number of important announcements varies along the x-axis. We see no matter the equity premium concentration or the number of important announcement, this method reveals the total equity premium attributable to the macroeconomic announcements. Also notice that this method naturally handles overlap in announcements and there is no need for the non-binary fixed effect or the separate fixed effects for each series to determine the equity premium concentration.

**Fig. 6. Simulation Equity Premium Concentration from Fixed Effects** This figure shows the median percent of the equity premium revealed by a single fixed effect for the macroeconomic announcement series from 10,000 simulation runs. Panel A shows when the fixed effect is used for all 21 possible macroeconomic announcment series. The red, blue and green lines show the results when the simulation is calibrated to attribute 30, 60 and 80 percent of the equity premium to the important macroeconomic announcment series. Panel B shows when the fixed effect is used for ex-post (within each simulation) determined subsets of the 21 possible macroeconomic announcement series. In Panel B the simulation is calibrated to attribute 60 percent of the equity premium to the important macroeconomic announcment series. The red, blue and green lines show the results for subsets of size 1, 3 and 5. For both panels the regression run is the daily market return on a constant and a fixed effect that is 1 if any of the considered macroeconomic announcments occur that day and zero otherwise. The vertical axis in both panels plots the percent of the equity premium, which is the fixed effect coefficient times the fraction of the days which have a positive macroeconomic fixed effect. The horizontal axis marks the number of important macroeconomic announcement series. See Figure 5 for further details of the simulations and calibration.




Panel A: Fixed effect regression concentration from all macro announcements




Panel B: Fixed effect regression concentration from ex-post subsets of macro announcements

## 2.16 Ex-post Identified Sets Do Not Reveal Equity Premium Concentration

The ability to determine the equity premium due to the macroeconomic announcements is not due solely to the fixed effect regression but to including all plausibly important announcement series. Using the fixed effect regressions with the subsets of announcement series with high realized returns does not reliably deliver this concentration.

Panel B shows the median concentration from such fixed effect regressions across simulations for subsets of size 1, 3 and 5 (red, blue and green) when the equity premium concentration in the important announcements is 60%. We see that as we vary the number of important announcement across the x-axis, we only obtain the actual equity premium concentration in the special case of a subset of size 1 when there is one important announcement series. These results are similar to the inability of the raw concentrations from subsets to reveal the information.

## 2.17 The CAPM Fit

In this section, we show that the literature's finding that the CAPM "fits better" on announcement days is not a separate piece of evidence that macroeconomic announcements are important. Higher slopes on the market return in cross-sectional regressions are a mechanical by-product of the higher realized returns on those days.

## 2.18 What Does the Market Premium From Cross-Sectional Regression Reveal?

The CAPM makes the prediction that exposure to the market explains all cross-sectional differences in expected returns. Finding a negative cross-sectional premium refutes the CAPM, but finding a positive cross-sectional market premium does not validate the CAPM. Early tests of the CAPM used market premium slopes, but crucially in such tests they measured whether the slopes on *other* explanatory variables were non-zero as the test of the CAPM (e.g., Fama and MacBeth, 1973). The current more general methodology uses pricing errors or cross-sectional $R^2$ to test the CAPM. The connection between these two methods is that low pricing errors (high cross-sectional $R^2$) mean there is little scope for additional variables to contribute to cross-sectional explanations of expected returns, i.e., the slopes on additional factors should be zero.

Studies have found, in some periods and tests assets, a negative market premium. This negative slope can be attributed to omitted factors when the market premium is used as the sole explanation of cross-sectional returns. The positive market premium from cross-sectional regressions can typically be restored by including the omitted factors. The question regarding the CAPM is not whether the equity premium is positive nor whether there is positive relation between market risk exposure and expected returns once confounding factors have been controlled for. Virtually all return based factor models include the market return as a factor because of its recognized importance in explaining the cross-section of returns (e.g., Fama and French, 1992b; Carhart, 1997; Fama and French, 2015; Stambaugh and Yuan, 2017). The question about whether the CAPM fits is one of pricing errors.

So what then does the market premium (slope) from cross-sectional regression on different sets of days tell us, if these slopes are not even a test of the conditional CAPM? It might be thought that cross-section premium can reveal the expected return on these days. Unfortunately, whenever the market return contributes to cross-sectional expected returns–even in the presence of other important factors as is the known case–this slope does not separate expected returns from realized returns any better than the time series average of the market return does. This inability to separate expected returns from realized returns is because this regression slope is mechanically driven by the realized returns not the expected returns.

**Derivation of cross-sectional premium's dependence upon realized returns**

To see that these slopes mechanically reproduce the information contained in ex-post market returns, consider the following return generating process for the test assets:

$$r_{i,t} = a_i + \beta_i r^e_{m,t} + \theta_{i,t} \tag{14}$$

where for simplicity of illustration $\theta_{i,t}$ is independent of the market excess return. Importantly, this return generating process does *not* say the CAPM holds. It merely says that returns on the test assets co-move with the market, a fact undeniable in the data.

Let the estimated market beta at any time $t$ be $\hat{\beta}_{i,t}$. This estimate is the true beta plus some measurement noise $\beta^*_{i,t}$. Consider the cross-sectional regression run on these test assets each period $t$:

$$r_{i,t} = c_t + \lambda_t \hat{\beta}_{i,t} + \psi_{i,t}. \tag{15}$$

Substituting in the return generating process and splitting the beta estimate into its true and noise components gives

$$a_i + \beta_i r^e_{mkt,t} + \theta_{i,t} = c_t + \lambda_t(\beta_i + \beta^*_{i,t}) + \psi_{i,t}. \tag{16}$$

Assuming the beta estimation error has zero correlation with the return $r_{i,t}$, we derive the cross-sectional premium:[21]

$$\lambda_t = w_m r^e_{mkt,t} + (1 - w_m) \times 0 \tag{17}$$

where the weights are determined by the standard attenuation bias formula:

$$w_m = \frac{\sigma^2_{CS}(\beta)}{\sigma^2_{CS}(\beta) + \sigma^2_{CS}(\beta^*)} \tag{18}$$

[21] From equation 16, we can define the regression coefficient as

$$\lambda_t = \frac{cov[\beta_i + \beta^*_{i,t}, a_i + \beta_i r^e_{mkt,t} + \theta_{i,t}]}{var[\beta_i + \beta^*_{i,t}]},$$

which immediately leads to equations 17 and 18 above. The result goes through without zero correlation, simply replacing the zero in the following equation with the appropriate noise coefficient to reflect the non-zero correlation.

where $\sigma^2_{CS}$ stands for the cross-sectional variances of the betas and its measurement noise. Thus we see that the cross-sectional coefficient is mechanically increasing in the realized market return on a given day or set of days.

If the test assets' market betas differ across the sets of days this would introduce differential noise in the beta estimates across the sets of days when betas are estimate across the days. This would introduce further variation in the slopes beyond the market return realizations. However the literature has shown that the betas are similar across the previously studied announcement and non-announcement days (Savor and Wilson, 2014).

Decomposing realized returns into expected returns plus realized noise shows higher expected returns all else equal give higher slopes. Thus higher slopes on announcement days are consistent with the concentration hypothesis. However, the crucial point is that the realized market return can be high simply due to random realizations. Both outcomes give higher estimated CAPM premia. Because of this effect, running Fama-MacBeth regressions across announcement days merely picks up the higher average realized returns on those days.

## 2.19 Prior Literature's Results Hold in this Sample

Savor and Wilson (2014) state that, if the news on macroeconomic days is particularly important, then the CAPM should work better on those days since those are days when the market news is more important. They write "on days when news about inflation, unemployment, or Federal Open Markets Committee (FOMC) interest rate decisions is scheduled to be announced, stock market beta is economically and statistically significantly related to returns on individual stocks." This could be true if there really were higher expected returns on these announcement days, but it can also be true if returns on these days are higher merely by luck. Cross-sectional regressions cannot separate these two hypothesis. We do not dispute the literature's findings merely the interpretation.

In fact we replicate their main result in our sample period using the same test assets. We follow their procedure for creating beta-sorted portfolios and we obtain the 25 size and

**Table 16**
**CAPM Cross-sectional Regression Slopes for Announcement and Non-Announcement Days** This table reports average slope estimates from Fama-MacBeth regressions of daily excess returns on estimated betas for various test portfolios. Announcement days include only days with scheduled inflation news and unemployment news, and with or without FOMC interest rate decisions. Non-announcement days include all other days. The set of test assets are 45 portfolios that include 10 beta sorted portfolios, 10 Fama French industry portfolios and 25 size and book to market sorted portfolios. For brevity, we do not report the average intercepts of the regressions nor tests of the difference between announcement and non-announcement days. Standard errors are in parentheses, and *, ** and *** indicate significance at the 10, 5 and 1 percent levels. $R^2$ values are the averages of the values across the Fama-MacBeth regressions. The sample period is January 1990 to June 2018. This table replicates the results of Table 1 Panel C of Savor and Wilson (2014), so see that paper for further methodological details.

| | Without FOMC | | With FOMC | |
|---|---|---|---|---|
| | Slope | $R^2$ | Slope | $R^2$ |
| Announcement days | 0.00081 | 0.288 | 0.00117*** | 0.281 |
| | (0.00050) | | (0.00044) | |
| Non-announcement days | -0.00014 | 0.258 | -0.00022 | 0.257 |
| | (0.00016) | | (0.00016) | |

book-to-market sorted portfolios and ten industry portfolios from Ken French's website. Their main measure of fit is the average slope of the CAPM coefficient, i.e., premium, in cross-sectional regressions. Table 16 shows these market beta slopes on these 45 test assets, which are obtained from running Fama-MacBeth regressions on announcement and non-announcement days separately. We follow their procedure for estimating the test assets' betas each day using a rolling one-year window. (Appendix Table 23 shows the results for the subsets of test assets.)

The main result holds in that the CAPM slope coefficient is significantly larger on announcement days compared to non-announcement days. This difference is particularly large when using all three macroeconomic variables (inflation, unemployment and FOMC) but significantly smaller when the FOMC is not included. The point estimates on announcement days are larger in our more recent sample period compared to their original result (0.0012 in our table versus 0.00087 in their Table 1's Panel C).

It is worth noting that Savor and Wilson (2014) do not use pricing errors as measure of the differential performance of the CAPM between announcement and non-announcement days. The pricing errors across these two sets of days are virtually identical as can be seen in the near identical average cross-sectional $R^2$ presented in their Table 1 Panel C (30.3% on announcement days versus 28.4% on non-announcement days). We find the same result in our sample. Table 16 shows cross-sectional $R^2$ are 28.1% for these announcement days and 25.7% for the non-announcement days. The similarity in $R^2$ indicates that the CAPM does an equally good job pricing assets on both sets of days.

In summary, the above Fama-MacBeth CAPM slope results do not show that macroeconomic announcement days are special beyond the information already presented that ex-post market returns are higher on these days.[22]

## 2.20 Market Premia Varies Across Announcement Series with Realized Returns

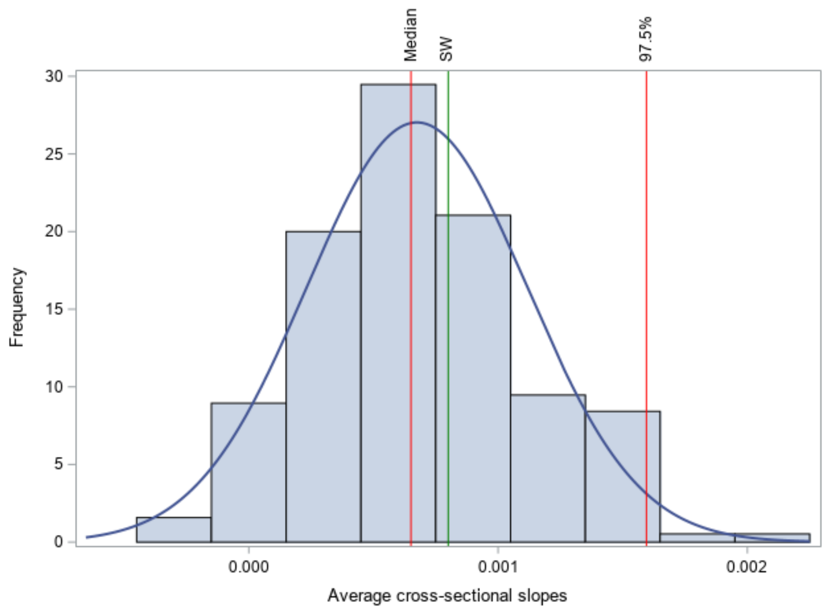
As we have shown earlier the announcements of the FOMC, unemployment and inflation do not appear particularly special relative to other macroeconomic announcement series. Cross-sectional CAPM regressions on these announcement days reveal no additional evidence of specialness. To see that many combinations of announcements deliver high slopes in these regression, we repeat a procedure analogous to that in Figure 4 for the time series average market returns on different combinations of announcement series.

Figure 7 presents distributions of average Fama-MacBeth CAPM slope coefficients for all possible combinations of two (Panel A) or three (Panel B) macroeconomic announcement variables. Appendix Table 24 shows the summary statistics for these distributions. The green lines mark where the announcments considered by Savor and Wilson (2014) fall in the distributions. We see that unemployment and inflation fall at the 65th percentile and the combination including the FOMC falls the 89th percentile. Many other combinations of three macroeconomic variables deliver higher premia. For comparison these announcement days fell at the 70th and 91st percentiles of the average market returns.

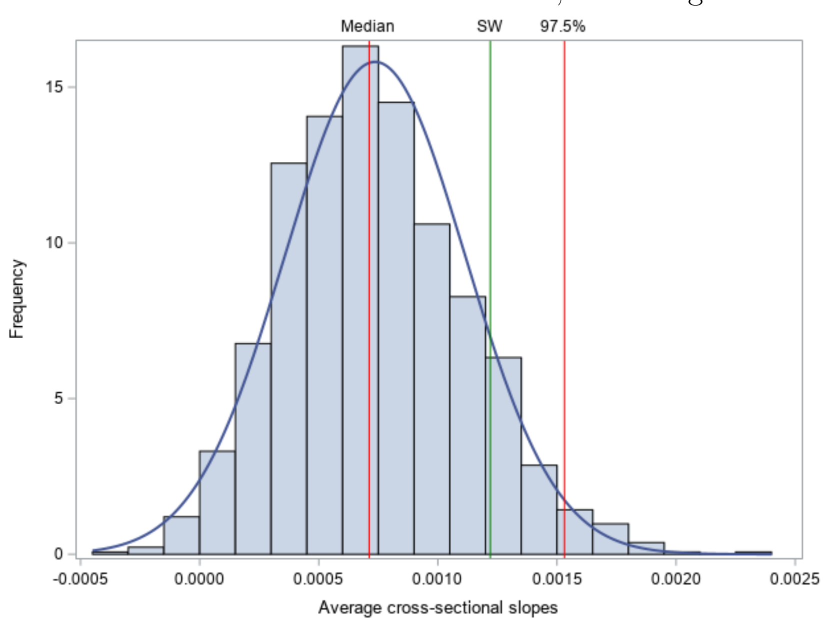
More broadly, these distributions echo those of the average market return (Figure 4). We

[22] Franzoni and Schmalz (2017) show that alphas are more visible when the factor realizations (market returns) are low. We show that alphas/slopes are less/more visible when market returns are large.

**Fig. 7. Histograms of Average Cross-Sectional Slopes on Announcement Days** This figure shows histograms of average cross sectional slopes on announcement days for every combination of two or three macroeconomic variables. Panel A is the histogram from selecting 2 variables, excluding the FOMC. Panel B is the histogram from selecting 3 variables, including the FOMC. The set of test assets are all 45 portfolios. The green line shows the values for the combination of annoucements in Savor and Wilson (2014). The red lines show the median and 97.5th percentile values.




Panel A: Two macroeconomic variables, excluding FOMC




Panel B: Three macroeconomic variables, including FOMC

see this strong positive association in the scatter plots of the cross-sectional slope and the realized equity premium on announcement days. Panels A and B of Figure 8 show scatter plots with the average market return on the x-axis and the cross-sectional slopes on the y-axis. Panel A plots combinations of 2 announcement series and Panel C plots combinations of 3. That higher average market returns comes with higher CAPM slope estimates confirms the mechanical relation we derived between the two. In fact the slope of the best fit line in these scatter plots is essentially 1.

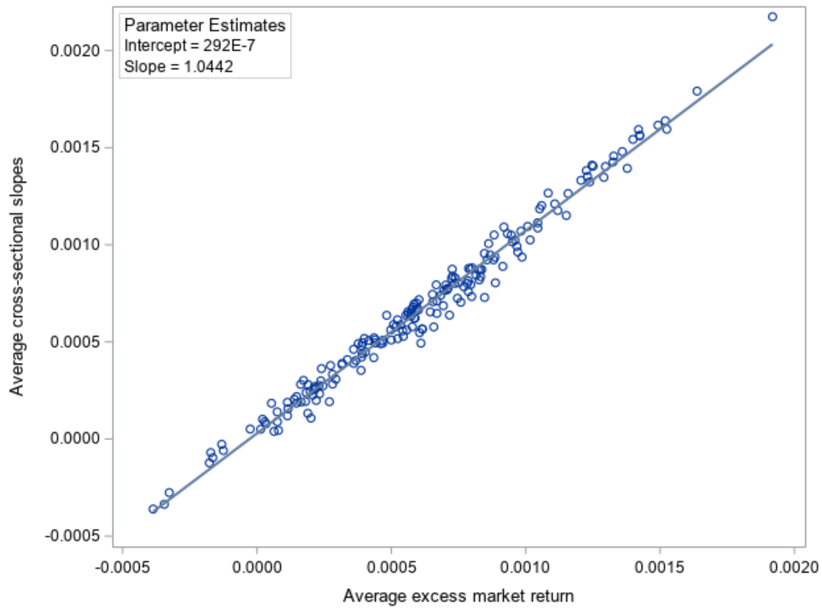
## 2.21 Sorting Days by Market Return Shows Mechanical Relation

To further illustrate that cross-sectional CAPM slopes are merely a mechanical reflection of the realized market returns, we sort days in our sample into deciles based on the realized market return on those days. We then run Fama-MacBeth CAPM regressions on each of these deciles of days. Table 17 shows that the CAPM premium estimates are monotonically increasing in the market return decile, as predicted. This increase occurs for all test assets and explains the robustness of Savor and Wilson's finding across a large variety of test assets.[23]

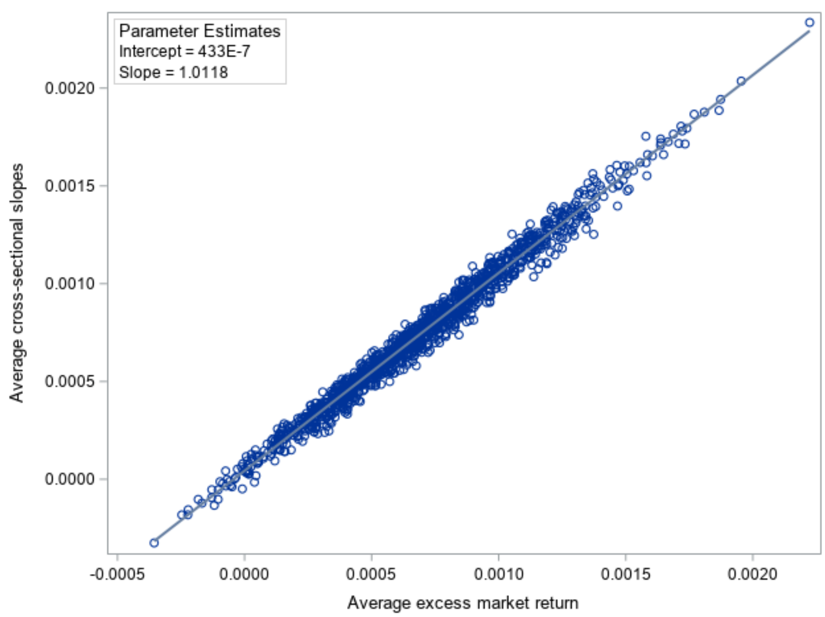
As long as there is a spread in betas on a set of test assets large enough relative to the estimation noise then one will obtain higher CAPM premia on days with larger market returns. These higher premia do not show that the CAPM fits better (pricing errors are not lower) nor do these higher premia show that "the cross-sectional patterns and the nature of the aggregate risk-return trade-off are completely different depending whether there is a pre-scheduled release of important information to the public."

[23] Savor and Wilson show that they do not get higher premia on large market move days. Importantly, they consider the largest *absolute* value of market moves. This effectively averages the top and bottom returns, giving approximately a zero average realized return. This zero average realized return thus gives a zero cross-sectional premium.

**Fig. 8. Scatter Plots of Average Excess Market Returns and Average Cross-Sectional Slopes on Announcement Days** This figure shows scatter plots of the average excess market returns and average cross sectional slopes on announcement days for every combination of two or three macroeconomic variables. Panel A is the scatter plot from selecting 2 variables, excluding the FOMC. Panel B is the scatter plot from selecting 3 variables, including the FOMC. The blue line shows the best fit line. The set of test assets are all 45 portfolios.




Panel A: Two macroeconomic variables, excluding FOMC




Panel B: Three macroeconomic variables, including FOMC

**Table 17**
**CAPM Fit by Market Return Deciles** This table provides the average CAPM slope coefficients from Fama-Macbeth regressions for deciles of days ranked by excess market returns, where decile 1 (10) represents the lowest (highest) decile of market return days. The set of test assets are the ten portfolios sorted by market beta, the 25 Fama-French portfolios sorted by size and book-to-market, and the ten Fama-French industry portfolios, all value-weighted. Standard errors are in parentheses, and *, ** and *** indicate significance at the 10, 5 and 1 percent levels.

| Decile | Beta Sorted | FF 25 | FF Industry | All |
|---|---|---|---|---|
| 1 | -0.020*** | -0.019*** | -0.020*** | -0.020*** |
| | (0.000) | (0.001) | (0.001) | (0.000) |
| 2 | -0.009*** | -0.010*** | -0.009*** | -0.008*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 3 | -0.005*** | -0.005*** | -0.005*** | -0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 4 | -0.003*** | -0.003*** | -0.003*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 5 | -0.001*** | -0.001*** | 0.000 | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 6 | 0.001*** | 0.001*** | 0.002*** | 0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 7 | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 8 | 0.005*** | 0.004*** | 0.004*** | 0.005*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 9 | 0.009*** | 0.009*** | 0.009*** | 0.009*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 10 | 0.021*** | 0.020*** | 0.020*** | 0.019*** |
| | (0.001) | (0.001) | (0.001) | (0.000) |

## 2.22 Conclusion

This paper addresses the puzzling fact that existing published papers have together documented well over 100% of the equity premium being earned on a small set of macroeconomic announcement days. This greater than 100% of the equity premium leaves no room for other systematically important announcements such as earnings. Moreover, if macroeconomic announcements were truly responsible for more than 100% of the equity premium, then an investment in the market must earn predictably negative expected returns for the majority of the year.

We build on the insights of Fama and French (2010) that looking at the entire distribution of managers can provide information that cannot be obtained simply by looking at ex-post good performance and the insights of Kelly and Jiang (2014) that one can use the cross-section of similar events to effectively lengthen the time-series observations. We ask how much of the equity premium is attributable to all monthly macroeconomic variables (and the FOMC) rather than looking only at variables with relatively high ex-post returns.

This entire distribution contains an above average concentration of the equity premium, consistent with the literature's conclusion that macroeconomic announcements contain above average information in expectation. Exploiting the whole distribution and controlling for the day-of-the-month effect shows that macroeconomic announcements as a whole are responsible for about 60% of the equity premium. Importantly this premium is earned over 62% of trading days rather than only a small set of days previously considered.

Solving this too-much-return puzzle also addresses the complementary excess Sharpe ratio puzzle on macroeconomic announcement days. Finally, we show that the "improved" fit of the CAPM on announcement days as measured by higher premia measured from cross-sectional regressions is a mechanical reflection of the higher realized returns on these days. The higher premia thus do not represent a separate piece of information as to the importance of macroeconomic announcements.

Throughout all the results of this paper, the FOMC appears to stand out from the other macroeconomic announcements. It has among the largest point estimates for the concentration of the equity premium. It also often has the only statistically significant fixed effect. However, the joint test of significance of all the macroeconomic announcement fixed effects including the FOMC, Equation (13), yields an insignificant P-value. This means one should interpret this large point estimate and lone significance with caution. The lack of joint significance means such an outcome is a reasonably plausible one from testing across many macroeconomic announcements. Further simulations show concentration in a single announcement series such as the FOMC is likely even if it is ex-ante identical to the other 21 announcement series.

Nevertheless, perhaps one important difference between the FOMC and all the other variables is that the FOMC is also about actions to be taken in the financial markets (or inaction), and not only information about the (past) state of the economy. Or perhaps the FOMC is a summary statistic of all other variables (Gilbert et al., 2012). Or perhaps the FOMC is more forward looking while all other variables are backward looking (Kadan and Manela, 2018). If there is indeed any difference, explaining it is beyond the scope of this paper, and we leave it for future research (Jarociński and Karadi, 2019).

## 2.23 Appendix

**Table 18**
**Replicating and Decomposing Savor and Wilson (2013)** This table reports the average market excess return on inflation (PPI), employment, and FOMC days (Ann.) versus all other days (Non-ann.), as well as the difference between the two (Diff.). We also report the percent of the equity premium earned on those days in the last column (see Equation 9). The first row replicates the main result from Savor and Wilson (2013) during our sample period (January 1990 - June 2018). The second row excludes the FOMC and the third row includes only the FOMC. The non-announcement day columns are kept constant across all rows. Standard errors are in parentheses, and *, ** and *** indicate significance at the 10, 5 and 1 percent levels.

| | Average return | | | |
|---|---|---|---|---|
| | Ann. | Non-ann. | Diff. | Percent of EP |
| Updated Savor and Wilson (2013) | 12.5*** | 1.8 | 10.7*** | 57.3% |
| | (3.71) | (1.34) | (3.96) | |
| Only unemployment and inflation | 8.1* | 1.8 | 6.3 | 26.5% |
| | (4.33) | (1.34) | (4.42) | |
| Only FOMC | 27.0*** | 1.8 | 25.2*** | 31.9% |
| | (7.22) | (1.34) | (7.33) | |

**Table 19**
**Single Macroeconomic Announcement Fixed Effect: Count Simultaneous Announcements** This table records the coefficient estimates from the fixed effects regressions with a single fixed effect that is equal to the sum of all macroeconomic announcements on a given day (e.g., 0, 1, 2, 3, ...). This is consistent with treating all macroeconomic announcements the same ex-ante, but allowing multiple announcement to have a cummulative news effect. The baseline specification is:

$$r^e_{m,t} = \alpha + \phi_{all}\mathbb{1}(Macro_{all}) + \varepsilon_t$$

and the full specification is:

$$r^e_{m,t} = \phi_{all}\mathbb{1}(Macro_{all}) + \sum_{j=-9}^{9} \gamma_j \mathbb{1}(Tradeday_j) + \varepsilon_t.$$

Panel A shows the fixed effect of the macroeconomic announcements for both specifications along with the intercept for the first specification. Panel B shows the day-of-month fixed effects. It also shows the average day-of-month fixed effect where the Mid fixed effect is counted 3 times consistent with its average appearance (for an average of 21 day per month). For ease of interpretation daily returns are divided by the average daily equity premium. Standard errors are in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent levels.The F-test for joint significance of the day-of-the-month fixed effects P-value is 0.0921.

Panel A: Fixed effect on the macroeconomic announcements

| | Day of the month fixed effects | |
|---|---|---|
| | Excluded | Included |
| $\phi_{all}$ | 1.19*** | 0.47 |
| | (0.41) | (0.49) |
| $\alpha$ | -0.16 | |
| | (0.57) | |

Panel B: Fixed effects on the days of the month

| Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ |
|---|---|---|---|---|---|
| 1 | 4.49** | 8 | -0.70 | -6 | -2.45 |
| | (2.20) | | (1.87) | | (1.87) |
| 2 | 1.56 | 9 | 3.14 | -5 | -1.47 |
| | (1.92) | | (2.00) | | (1.89) |
| 3 | 0.29 | Mid | 1.90 | -4 | 4.21** |
| | (1.89) | | (1.30) | | (1.91) |
| 4 | -0.05 | -9 | -0.31 | -3 | 2.69 |
| | (1.88) | | (1.91) | | (1.91) |
| 5 | -2.07 | -8 | -0.81 | -2 | 2.56 |
| | (1.98) | | (1.90) | | (1.90) |
| 6 | -1.17 | -7 | -4.37** | -1 | 1.28 |
| | (1.86) | | (1.88) | | (1.95) |
| 7 | -1.16 | | | | |
| | (1.87) | | | | |
| Average FE | 0.55 | | | | |
| | (NA) | | | | |

**Table 20**

**Concentration of Equity Premium Implied by Fixed Effects** This table shows the cumulative percent of the equity premium earned by investing in the market on subsequent combinations of macroeconomic variables. Column 1 reports the macroeconomic fixed effects (FE) coefficients from the regression with only the macroeconomic announcement fixed effect and column 2 reports the estimates with the day-of-the-month fixed effects included. The rows are sorted by the magnitude from the regression without the day-of-the-month fixed effects. The cumulative arithmetic sum of the annual percent of the equity premium is calculated for each specification (columns 3 and 4). Column 5 records the cumulative sum of announcement events used divided by the total number of observations. Column 6 reports the cumulative sum of the percentage of the equity premium earned following the geometric methodology in Table 9. Column 7 repeats the exercise in Column 6 but using a daily market return time series that is purged of the day-of-the-month fixed effects. Column 8 reports the fraction of days with announcements. (Overlapping announcements count as 1 day.)

| | Arithmetic Averages | | | | | Geometric Averages | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Variable | Without DOM FE | With DOM FE | Without FE Sum | With FE Sum | #Ann. / #Obs. | Without % of EP | With % of EP | % of days invested |
| Construction Spending | 8.20 | 7.30 | 0.39 | 0.34 | 5% | 36.2% | -22.6% | 4.7 % |
| FOMC | 7.50 | 7.25 | 0.63 | 0.58 | 8% | 68.1% | 5.9% | 7.8 % |
| Consumer Confidence | 2.96 | 0.90 | 0.77 | 0.62 | 13% | 88.1% | 14.1% | 12.0% |
| Unemployment Rate | 2.92 | 3.42 | 0.91 | 0.78 | 17% | 104.3% | 39.2% | 16.3% |
| Advance Retail Sales | 2.82 | -0.01 | 1.04 | 0.78 | 22% | 117.4% | 30.1% | 20.9% |
| Housing Starts | 2.18 | 1.84 | 1.15 | 0.87 | 27% | 122.4% | 30.2% | 25.2% |
| New Home Sales | 2.00 | 1.75 | 1.24 | 0.95 | 32% | 141.1% | 46.1% | 29.0% |
| PPI | 1.88 | 1.39 | 1.33 | 1.02 | 37% | 149.6% | 49.8% | 31.8% |
| Capacity Utilization | 1.84 | -0.03 | 1.42 | 1.01 | 41% | 149.4% | 39.0% | 34.7% |
| UM Consumer Confidence F | 1.57 | 0.79 | 1.49 | 1.06 | 46% | 150.8% | 35.4% | 38.0% |
| Trade Balance | 1.26 | 1.19 | 1.55 | 1.11 | 51% | 154.9% | 40.0% | 41.8% |
| Durable Goods | 1.07 | 0.54 | 1.60 | 1.14 | 56% | 159.0% | 41.7% | 44.4% |
| Factory Orders | 0.65 | 0.54 | 1.64 | 1.17 | 60% | 158.4% | 41.1% | 47.8% |
| CPI | 0.29 | -0.54 | 1.65 | 1.14 | 65% | 157.1% | 37.1% | 49.4% |
| Personal Consumption | -0.19 | -0.72 | 1.64 | 1.10 | 70% | 155.3% | 32.4% | 50.8% |
| Leading Indicators | -0.86 | -0.21 | 1.60 | 1.09 | 75% | 145.3% | 26.7% | 53.8% |
| Business Inventory | -1.55 | -2.78 | 1.53 | 0.96 | 79% | 144.7% | 22.7% | 54.7% |
| Monthly Budget Statement | -1.62 | -0.61 | 1.45 | 0.93 | 84% | 134.7% | 17.5% | 57.7% |
| NAPM | -2.22 | -12.90 | 1.34 | 0.32 | 89% | 136.0% | 13.8% | 58.0% |
| Consumer Credit | -2.26 | 1.64 | 1.23 | 0.39 | 94% | 122.7% | 15.9% | 61.0% |
| UM Consumer Confidence P | -2.32 | -3.23 | 1.12 | 0.24 | 98% | 121.0% | 13.2% | 61.6% |
| All Macro Variables | | | 112% | 24% | 98% | 121.0% | 13.2% | 61.6% |

**Table 21**
**Single Macroeconomic Announcement Fixed Effect Omitting Limited Variation Series** This table records the coefficient estimates from the fixed effects regressions with a single fixed effect that is equal to 1 if there is any macroeconomic announcement on a given day. This is consistent with treating all macroeconomic announcements the same ex-ante. The baseline specification is:

$$r^e_{m,t} = \alpha + \phi_{all}\mathbb{1}(Macro_{all}) + \varepsilon_t$$

and the full specification is:

$$r^e_{m,t} = \phi_{all}\mathbb{1}(Macro_{all}) + \sum_{j=-9}^{9}\gamma_j\mathbb{1}(Tradeday_j) + \varepsilon_t.$$

The three series with limited variation in their announcement timing across the day-of-month are omitted: Construction Spending, NAPM and Consumer Credit. Panel A shows the fixed effect of the macroeconomic announcements for both specifications along with the intercept for the first specification. Panel B shows the day-of-month fixed effects. It also shows the average day-of-month fixed effect where the Mid fixed effect is counted 3 times consistent with its average appearance (for an average of 21 day per month). For ease of interpretation daily returns are divided by the average daily equity premium. The F-test for joint significance of the day-of-month fixed effects has P-value of 0.0413. Standard errors are in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent levels.

Panel A: Fixed effect on the macroeconomic announcements

| | Day of the month fixed effects | |
|---|---|---|
| | Excluded | Included |
| $\phi_{all}$ | 1.94** | 1.15 |
| | (0.82) | (0.88) |
| $\alpha$ | -0.08 | |
| | (0.61) | |

Panel B: Fixed effects on the days of the month

| Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ | Day | $r^e/\bar{r}$ |
|---|---|---|---|---|---|
| 1 | 5.15*** | 8 | -0.99 | -6 | -2.66 |
| | (1.90) | | (1.94) | | (1.90) |
| 2 | 1.28 | 9 | 2.95 | -5 | -1.73 |
| | (1.95) | | (1.98) | | (1.91) |
| 3 | 0.02 | Mid | 1.71 | -4 | 3.90** |
| | (1.91) | | (1.27) | | (1.95) |
| 4 | -0.28 | -9 | -0.61 | -3 | 2.33 |
| | (1.90) | | (1.94) | | (1.95) |
| 5 | -1.86 | -8 | -1.13 | -2 | 2.26 |
| | (1.90) | | (1.94) | | (1.93) |
| 6 | -1.23 | -7 | -4.64** | -1 | 0.97 |
| | (1.86) | | (1.90) | | (1.97) |
| 7 | -1.29 | | | | |
| | (1.87) | | | | |
| Average FE | 0.36 | | | | |
| | (NA) | | | | |

**Table 22**
**Simulation Percentiles Including Extra Announcment Series** This table records the 2.5, 50 and 97.5 percentiles for the 10,000 simulation runs in Panels A, B and C. Values are the percent of the equity premium (geometric averages) accounted for by the subset of the ex-post highest 1, 2, 3, 4 or 5 macroeconomic announcement series for each simulation chosen out of a possible 42 macroeconoic series. The larger total set of possible macroeconomic announcement series, captures the datamine inclusion of day before announcement or other "related" announcment days such as biweekly days between announcments. Subset size varies across the rows. For each simulation there are either 1, 3, 5, 7, 10, 15, or 21 important macroeconomic announcment series. These vary across the columns. The important macroeconomic anouncement series are the only series to earn any additional equity premium. The equity premium for each of these series is $\frac{1}{N}$ of the total equity premium attributable to the macroeconomic announcements, where $N$ is the number of important series. These equity premium and variance are earned in proportion and split linearly across the important marcoeconomic announcment series and all other days. The simulation is calibrated to assign 60% of the equity premium to the important macroeconomic announcement series. The total equity premium and market return variance is calibrated to match the acutal data: 7.96% and 17.30% annualized.

Panel A: 50th Percentile

| | Number of Important Announcements | | | | | | |
|---|---|---|---|---|---|---|---|
| Subset Size | 1 | 3 | 5 | 7 | 10 | 15 | 21 |
| 1 | 40.7 | 32.2 | 32.0 | 29.9 | 28.9 | 29.0 | 29.1 |
| 2 | 63.2 | 55.7 | 55.5 | 53.8 | 52.4 | 52.8 | 52.4 |
| 3 | 81.5 | 74.4 | 75.2 | 74.0 | 72.0 | 72.5 | 71.7 |
| 4 | 96.1 | 90.1 | 91.0 | 89.8 | 88.8 | 89.7 | 88.5 |
| 5 | 107.7 | 102.2 | 104.1 | 103.5 | 102.5 | 103.5 | 102.7 |

Panel B: 97.5th Percentile

| | Number of Important Announcements | | | | | | |
|---|---|---|---|---|---|---|---|
| Subset Size | 1 | 3 | 5 | 7 | 10 | 15 | 21 |
| 1 | 170.3 | 180.7 | 171.7 | 145.0 | 171.6 | 168.9 | 151.7 |
| 2 | 265.8 | 307.7 | 302.7 | 255.8 | 311.4 | 291.8 | 263.0 |
| 3 | 352.2 | 430.1 | 403.3 | 341.4 | 387.9 | 407.3 | 353.9 |
| 4 | 427.7 | 500.7 | 474.1 | 409.6 | 476.9 | 489.2 | 435.0 |
| 5 | 474.3 | 596.1 | 550.8 | 466.6 | 513.4 | 549.0 | 504.6 |

**Table 23**
**CAPM Cross-sectional Regression Slopes for Announcement and Non-Announcement Days: Subsets of Test Assets** This table reports average slope estimates from Fama-MacBeth regressions of daily excess returns on estimated betas for various test portfolios. Announcement days include only days with scheduled inflation news and unemployment news, and with or without FOMC interest rate decisions. Non-announcement days include all other days. The panels show the 3 subsets of test assets: 10 beta sorted portfolios, 10 Fama French industry portfolios and 25 size and book to market sorted portfolios. For brevity, we do not report the average intercepts of the regressions nor tests of the difference between announcement and non-announcement days. Standard errors are in parentheses, and *, ** and *** indicate significance at the 10, 5 and 1 percent levels. $R^2$ values are the averages of the values across the Fama-MacBeth regressions. The sample period is January 1990 to June 2018. This table replicates the results of Table 1 of Savor and Wilson (2014), so see that paper for further methodological details.

Panel A: Ten beta-sorted portfolios

| | Without FOMC | | With FOMC | |
|---|---|---|---|---|
| | Slope | $R^2$ | Slope | $R^2$ |
| Announcement days | 0.00098* | 0.54 | 0.00133*** | 0.532 |
| | (0.00051) | | (0.00044) | |
| Non-announcement days | 0.00007 | 0.509 | -0.00001 | 0.509 |
| | (0.00016) | | (0.00016) | |

Panel B: Fama-French 25 portfolios

| | Without FOMC | | With FOMC | |
|---|---|---|---|---|
| | Slope | $R^2$ | Slope | $R^2$ |
| Announcement days | 0.00110* | 0.217 | 0.00127** | 0.213 |
| | (0.00057) | | (0.00051) | |
| Non-announcement days | -0.00023 | 0.208 | -0.00030 | 0.208 |
| | (0.00020) | | (0.00020) | |

Panel C: Fama-French ten industry portfolios

| | Without FOMC | | With FOMC | |
|---|---|---|---|---|
| | Slope | $R^2$ | Slope | $R^2$ |
| Announcement days | 0.00055 | 0.273 | 0.00116** | 0.273 |
| | (0.00060) | | (0.00053) | |
| Non-announcement days | -0.00001 | 0.253 | -0.00012 | 0.252 |
| | (0.00020) | | (0.00020) | |

**Table 24**

**Summary Statistics of Distributions of Average Fama-MacBeth CAPM Slope Coefficients** This table shows summary statistics for the distributions of combinations of 2 or 3 macroeconomic announcement series presented in Figure 7. The set of test assets includes ten beta sorted portfolios, 25 Fama-French portfolios, and ten Fama-French industry portfolios, all value-weighted.

| | Two Announcements | Three Announcements |
|---:|---:|---:|
| Mean | 0.00067 | 0.00074 |
| Standard deviation | 0.00044 | 0.00038 |
| 25th percentile | 0.00036 | 0.00047 |
| Median | 0.00065 | 0.00071 |
| 75th percentile | 0.00092 | 0.00098 |
| 95th percentile | 0.00148 | 0.00138 |

# Chapter 3

# Product Market Competition, Organization Capital, and the Cross-section of Expected Returns

## 3.1 Introduction

Intangible capital is an increasingly important factor of production. One form of intangible capital, organization capital, is embodied in the firm's key employees, such that these key employees supply positive net present value ideas that the firm implements to increase value to shareholders. However, these key employees have the outside option to leave the firm and supply their positive net present value ideas to a competing firm when this option is greater than their inside value. As a result, they are able to extract rents from the shareholders since the shareholders do not own all of the cash flow rights. Eisfeldt and Papanikolaou (2013) show that organization capital is risky because there are systematic fluctuations in the division of surplus between key talent and shareholders, and as a result, it requires a risk premium.

I extend their intuition and hypothesize that a firm will only be exposed to this risk when there are viable opportunities for the key employees to exercise their outside option. If there are no opportunities for key employees to exercise their outside option, the firm will not be sensitive to this risk, even if they have a high level of organization capital.

One way to measure the opportunites of employees to exercise their outside option is through the degree of product market competition of a firm's industry. Consider an extreme example of a firm in a monopoly industry. By definition, this firm has no other competitors, and as a result the key employees have limited opportunities to exercise their outside option. Certainly, this does not mean the key employees will have no other opportunities because they could transfer inter-industry. However they will not have as many opportunities as a similar firm in a perfectly competitive industry. Therefore, the degree of product market competition is a reasonable way to measure these opportunities.

In this paper I study the joint effects of product market competition and organization capital on stock returns. Specifically, I ask: What is the effect of competition on the risk imposed by organization capital? My main hypothesis is that the risk imposed by organization capital is only prevelant in firms in more competitive industries, since these industries provide more opportunities for their key employees to excercise their outside option.

I use a conventional double-sorting approach to test this hypothesis empirically, and I show a robust and positive interaction between product market competition and organization capital on stock returns. I measure organization capital and the degree of product market competition following standard methods in the literature (see Gu (1997) and Lev and Radhakrishnan (2013), respectively). I construct spread portfolios that are long firms with more organization capital relative to their peers and are short firms with more physical capital relative to their peers; I do this both for firms in the most competitive industries (high competition, high minus low organization capital) and in the least competitive industries (low competition, high minus low organization capital), where competition is measured by the Herfindahl-Hirschman Index (HHI). I find that the spread portfolio in the most competitive industries has average returns of 6.2% per year (t-stat of 2.89) and positive annual alpha of 6.79% (t-stat of 3.10), whereas the spread portfolio in the least competitive industries has positive but insignificant average returns of 1.2% per year (t-stat of 0.69) and positive but insignificant alpha of 1.63% per year (t-stat of 0.87). These results indicate that the risk imposed by high organization capital is only prevalent in highly competitive industries, where the key employees have more opportunities to exercise their outside option, and as a result extract rents from the shareholders. These results are robust to different methods of calculating HHI, different asset pricing models, and different quantile sorts.

If competition is driving these main results, then changes in the competitive environment should correlate with changes in the risk these firms face. If the overall level of competition decreases, then firms with high exposure to organization capital risk should become less risky since the ability for key employees to exercise their outside option decreases. I test this prediction by calculating the time series of average annual HHI and monthly conditional alphas for the spread organization capital portfolios in the highest and lowest quintiles of HHI. I find that monthly conditional alphas for firms in the highest quintile of HHI significantly increase when the aggregate level of competition decreases. This is consistent with the hypothesis that competition is driving the risk for high organization capital firms.

Finally, I use a different proxy for the ability of key employees to exercise their outside option: the enforceability of non-competition agreements. If non-competition agreements become easier to enforce, then the threat of key employees leaving the firm with their positive NPV ideas decreases because it is harder for them to switch jobs. As a result, firms with high levels of organization capital will become less risky because the risk of their key employees leaving will decrease. I test this hypothesis using a setting when three U.S. states (Texas, Louisiana, and Florida) had changes in the enforceability of their non-competition agreements. I find that the risk of high organization capital firms, as measured by expected returns, significantly decreased in Florida when enforceability of non-competition agreements increased, and significantly increased in Texas when the enforceability decreased. These results suggest that firms with high organization capital are riskier only when their key employees can viably exercise their outside option.

This paper extends the body of work related to the role of organization capital within a firm (Atkeson and Kehoe (2005), Prescott and Visscher (1980), Hall (2000), Carlin et al. (2011), Lustig et al. (2011)). Speciifically,I build on the work of Eisfeldt and Papanikolaou (2013). They construct a model that implies the differences in average returns for firms with high versus low organization capital arises due to the spread portfolio being negatively correlated with a systematic frontier technology shock. They show empirically that a two-factor model that includes the market and the spread portfolio prices the cross-section of firms sorted on organization capital. I replicate their original empirical results and show that they hold for my extended sample period. I then extend their work by sorting their original portfolios by the degree of product market competition and show that their results only hold for firms in the most competitive industries.

### 3.2 Data

Firms' monthly stock returns and accounting information are obtained from the Center for Research in Security Prices (CRSP) and the Compustat Annual Industrial Files for the sample period from 1963 to 2019. Following Eisfeldt and Papanikolaou (2013), the sample includes all non-financial firms with fiscal year ending in December, with common shares, that are traded on NYSE, AMEX and NASDAQ, with non-missing SIC codes, and with non-zero values of organization capital.

The direct measure of organization capital is calculated identically as in Eisfeldt and Papanikolaou (2013) using Selling, General, and Administrative (SG&A) expenditures. Their measure is motivated by Lev and Radhakrishnan (2013), who use SG&A to measure flows to organization capital. The stock of organization capital $O$ is calculated using the perpetual inventory method. Specifically, the stock of organization capital is calculated recursively by accumulating the deflated value of SG&A expenses:

$$O_{i,t} = (1-\delta_O)O_{i,t-1} + \frac{SGA_{i,t}}{cpi_t}, \tag{19}$$

where $cpi_t$ denotes the consumer price index. To implement the law of motion in Equation (1) the same growth rate $g$ and initial stock $O_0$ and depreciation rate $\delta_0$ is chosen. That is, the initial stock is calculated as:

$$O_0 = \frac{SGA_1}{g+\delta_O}, \tag{20}$$

The depreciation rate is set at 15%, which is equal to the depreciation rate used by the BEA in their estimation of R&D capital in 2006. The growth rate $g$ is set at 10%, which matches the average real growth rate of firm-level SG&A expenditures. The missing values in the

SG&A expense are treated as zero.

Further, to address the issue that accounting practices governing the exact compostion of SG&A vary across industries, firms are firstly ranked on organization to physical capital relative to their industry peers in the following way: firms are first sorted into 17 industries, given the Eugene and French (2016) classification. Then, within each industry, firms are sorted into 5 sub-portfolios based on the ratio of organization capital to book assets. The sub-portfolios are then pooled across industries to form 5 portfolios of firms sorted on $O/K$, where the breakpoints are industry-specific. Thus, portfolio 1 includes all the firms in the bottom quintile in terms of organization capital to assets in industry 1 through 17, etc.

I then, independently, rank firms on the degree of product market competition as measured by the Herfindahl-Hirschmann Index (HHI) using the same methodology as Gu (1997). The Herfindahl Index is defined as the sum of squared market shares:

$$HHI_{j,t} = \sum_{i=1}^{N_j} s_{i,j,t}^2, \tag{21}$$

where $s_{i,j,t}$ is the market share of firm $i$ in industry $j$ in year $t$, $N_j$ is the number of firms in industry $j$ in year $t$, and $HHI_{j,t}$ is the Herfindahl Index of industry $j$ in year $t$. The market share of an individual firm is calculated by using the firm's net sales divided by the total sales value of the entire industry. I classify industries with three-digit standard SIC codes from CRSP, and all firms with non-missing sales value are included in the sample to calculate the Herfindahl Index for a particular industry each year. I then assign firms into 5 portfolios using quintile breakpoints of the ranked values of Herfindahl Index in year $t-1$. I then use a conventional double-sorting approach to construct 25 portfolios with different characteristics in terms of the degree of competition and level of organization capital. Finally, I calculate monthly value-weighted returns on the 25 portfolios for the period from July of year $t$ to June of year $t+1$, and the portfolios are rebalanced in June of each year.

Table 25 shows the descriptive statistics for each of these 25 portfolios. The average of annual number of firms is relatively consistent across the portfolios and ranges from approximately 60 to 75, and there is no clear pattern of changes of average firm numbers across either organization capital or the HHI. Average market capitalization tends to decrease as the level of organization capital increases, which is consisitent with Eisfeldt and Papanikolaou (2013), however there is no apparent relation between average firm size and level of competition. As expected, average organization capital (competition) increase (decrease) monotonically along their respective sorts. Average HHI is very similar across portfolios of organization capital. This is due to first ranking firms on organization capital relative to their industry peers. That is, the firms in the highest level of organization capital contain the firms with the highest level of organization capital in each of the 17 Fama-French industries. However, there is still heterogeneity in HHI within each portfolio as well as (mechanically) across sorts on HHI.

From these 25 portfolios, I calculate two main spread portfolios of interest: The first is from the lowest quintile of firms sorted on the HHI index, which are firms in the most competitive industries (the HHI is scaled from 0 to 1, where an industry with an HHI value of 1 is a monopoly). I calculate the spread portfolio of high minus low organization capital for these firms and refer to this portfolio as HHL (high competition, high minus low organization capital). Similarly, I calculate the spread portfolio of high minus low organization capital from the highest quintile of firms sorted on the HHI, and refer to this portfolio as LHL (low competition, high minus low organization capital).

## 3.3 Results

This section tests the main hypothesis of the paper, such that the risk of organization capital is imposed on firms in highly competitive industries, and it is not imposed on firms in low competitive industries. I estimate the following model specifications:

$$R_t^{OMK} = \alpha^{OMK} + \beta^{OMK} R_t^{MKT} + \varepsilon_t^{OMK} \tag{22}$$

and

$$R_t^{HHL} = \alpha^{HHL} + \beta^{HHL} R_t^{MKT} + \varepsilon_t^{HHL} \tag{23}$$

and

$$R_t^{LHL} = \alpha^{LHL} + \beta^{LHL} R_t^{MKT} + \varepsilon_t^{LHL} \tag{24}$$

where $R_t^k$ is the monthly excess return of portfolios $k \in (OMK, HHL, LHL)$ and $R_t^{MKT}$ is the value-weighted market return minus the risk-free rate in month $t$.

Table 26 shows the results of these tests. The results from the first specification are a replication of the main empirical result from Table IV of Eisfeldt and Papanikolaou (2013). Over my longer sample period, I find qualitatively similar results: positive and significant excess returns on the spread portfolio of high-minus-low organization capital of 3.0% per year versus 4.6% per year. Similarly, I find positive and significant CAPM alphas of 3.9% versus 5.6%.

My main results show the return on the high minus low organization capital portfolio is positive and significant in competitive industries (HHL) and is positive but insignificant in concentrated industries (LHL). For example, the annual value-weighted return to the HHL portfolio is 6.2% and statistically significant at the 1% level. In contrast, this return is 1.2% with a t-statistic of 0.69 in concentrated industries. The CAPM alpha on the HHL portfolio is 679 basis points annually, and is significant at the 1% level (t-statistic of 3.10), whereas the alpha on the LHL portfolio is 163 basis points and is insignificant (t-statistic of 0.87).

The double-sorted portfolio results in Table 26 support the hypothesis that the positive organization capital return relation manifests itself in competitive industries, and it is not present in concentrated industries. Additionally, the positive and significant abnormal returns in competitive industries and positive but insignificant abnormal returns in concentrated industries suggests that firms with high organization capital are likely more exposed to this risk when the availability for their labor units to excercise their outside option is higher.

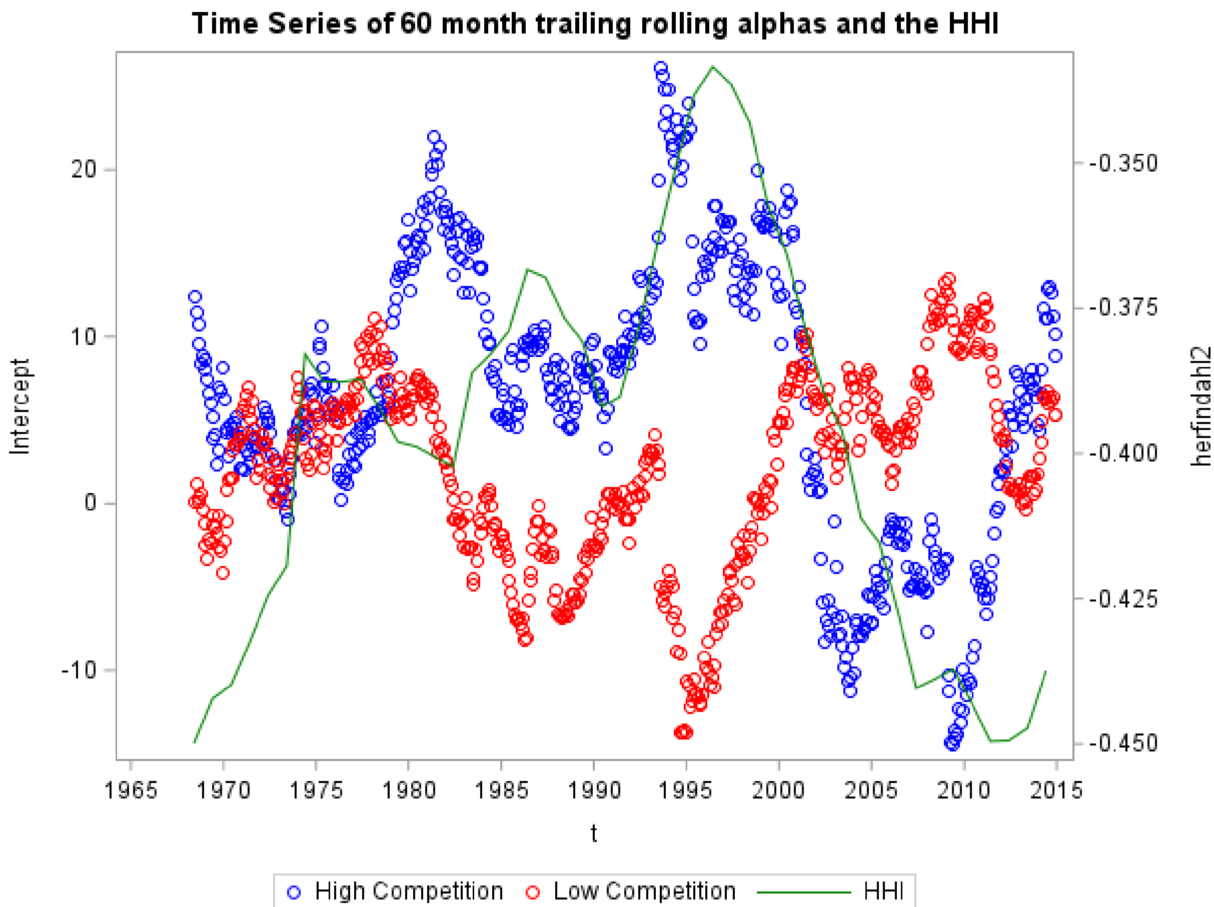
Table 27 shows the excess returns and CAPM alphas for each of the individual 25 dual-sorted portfolios. The difference in excess returns for the high minus low organization quintiles for the high (low) competition quintile of 9.163% minus 2.974% (7.797% minus 6.594%) represents the main result of 6.188% (1.202%) from table 26. Similarly, the differences in alphas for the same respective portfolios also correspond to the corresponding alpha values in table 26. Much of the variation in both average excess returns and portfolio alphas appears to exist between the fourth and fifth competition quintiles. For example, average excess returns in the fourth competition quintile are 7.587% and 6.181% in the high and low organization capital quintiles. However, they change to 9.163% and 2.974% in the fifth competition quintile. A similar situation occurs in the portfolio alphas. This suggests that the level of product market competition must be sufficiently high enough in order for this risk to be present.

## 3.4 Time Series of HHI and Portfolio Alphas

In this section, I investigate whether the mechanism of competition is driving the results of increased risk for firms with high organization capital. If the HHI accurately measures the degree of product market competition, and higher competition increases employees' abilities to exercise their outside option, then changes in the level of HHI will correlate with the change in the risk of firms with exposure to this risk. The HHI changes over time. As the HHI decreases, product market competition increases, and as a result, firms with high organization capital will be riskier since it will be easier for their employees to take their positive NPV ideas to competing firms since there will be more of these firms.

The annual average aggregate HHI is calculated by averaging the industry level HHI across all SIC codes each year. If changes in risk are driven by changes in the aggregate level of competition, then it is necessary to look at future alphas. Therefore, I calculate monthly conditional alphas for the high-minus-low organization capital portfolios of the highest and lowest quintiles of HHI (HHL and LHL) using 60 month forward rolling CAPM

**Fig. 9.** Time series of average annual aggregate HHI and monthly conditional alphas for the high-minus-low organization capital portfolios of the highest and lowest quintiles of HHI (HHL and LHL) using 60 month forward rolling CAPM regressions




regressions [24]. Figure 9 shows the time series of each of these. The green line is the inverted [25] HHI, such that increases in inverted HHI indicate higher levels of competition. The blue (red) dots show the monthly time variation in the conditional alphas for the high-minus-low organization capital portfolios of the high (low) quintile HHI portfolios.

I test the prediction that increases in competition are correlated to increases in risk for firms with high organization capital by averaging the monthly conditional alphas each year

[24]The results are robust to alternative windows. In the appendix I show the results hold for alphas calculated using prior 60 month returns.

[25]HHI is scaled from 0 to 1, and is decreasing in the level of competition (a value of 1 indicates only 1 firm in the industry, so there is no competition). I invert the HHI here by multiplying the HHI by -1 to have it increasing in the level of competition.

and running the following regression specification:

$$\alpha_t^j = \gamma_0 + \gamma_1 HHI_t + \varepsilon_t \tag{25}$$

for $j \in H, L$. Table 28 reports the results of these regressions. The positive and significant point estimate (145.04) on the HHI (inverted) for the alphas from the highest quintile of firms sorted on HHI indicates that the risk of these firms is positive and significantly related to the changes in the overall level of competition. This provides some evidence, but does not causally imply, that competition is associated with the risk of the firms with high levels of organization capital.

## 3.5 Enforceability of Non-compete Clauses and Organization Capital Risk

In this section, I utilize a quasi-natural experiment to show that the risk of higher organization capital is mitigated when the ability for labor inputs to utilize their outside option and take their NPV positive ideas to another firm is decreased using a differnt mechanism: the enforceability of non-compete contracts. While the degree of product market competition is one proxy for measuring this ability for employees to exercise their outside option, the literature has identified another measure of employee stability. Garmaise (2011) utilizes the time-series changes in state laws to show that increased enforceability in non-competition agreements reduces employee executive mobility. If executives with NPV positive ideas are in states whose enforceability of non-competition agreements increase, then their reduction in employee mobility would mitigate the organization capital risk to the firm since these employees are more likely to give their NPV ideas to their incumbent firm.

To test the prediction that increased enforceability of non-competition agreements will lead to a decreased risk from organization capital, I utilize the enforceabiltiy scores developed by Garmaise (2011), who develops them based on 12 questions analyzed by Marlsberger

(2004): The level of enforceability in Texas is 5 before 1994 and 3 thereafter; the score for Louisiana is 0 from 2002-2003 and 4 otherwise; the score for Florida is 7 before 1997 and 9 afterwards. These scores are only available from 1992-2004, therefore the *Post* variable in the following regression is 1 for Texas between 1995-2004, 1 for Louisiana from 2002-2003, and 1 for Florida from 1997-2004, and zero otherwise.

For each state, I estimate the following triple-difference regression model:

$$Y_{i,t} = \alpha_0 + \alpha_1 Treat1 + \alpha_2 Treat2t + \alpha_3 PostXTreat1 + \alpha_4 PostXTreat2$$
$$+\alpha_5 Treat1XTreat2 + \alpha_6 PostXTreat1XTreat2 + \gamma_i + \sigma_t + \varepsilon_{i,t}$$

where $Y$ is the expected return of firm $i$ calculated using the conditional Fama French 3 factor model at time $t$, $Treat1$ is equal to 1 if firm $i$ is located in the state where the change in enforceability took place, $Treat2$ is equal to 1 if the firm is above the median in Organization Capital, and $\gamma_i$ and $\sigma_t$ are firm and year fixed effects, respectively. The $Post$ variable is subsumed by the time fixed effects and is therefore not included in the model on its own.

The hypothesis that increased enforceability of non-competition agreements will lead to a decrease in the ability of employees to exercise their outside option, and subsequently a decrease in risk for firms with high organization capital suggests that the coefficient $\alpha_6$ will be higher in Texas and Louisiana and lower in Florida. This is due to enforceability decreasing during the post period in Texas and Louisiana and increasing for Florida during the post period.

Table 29 shows the results for each of these three regressions. Pursuant to the hypothetical prediction, firms in Texas with high organization capital during this sample period have 0.0043 significantly higher expected returns than all other firms during this sample period when Texas decreased the enforceability of non-competition agreements. This suggests that these firms had an increase in risk relative to other firms who had lower levels of organization capital when Texas made it more difficult to enforce non-compete clauses, and therefore made it easier for employees to exercise their outside options. The positive sign of the point estimate on $\alpha_6$ for Louisiana suggests a similiar outcome for similar firms in this state, however these results are not significant. Finally, and pursuant to the hypothetical prediction, firms in Florida with high organization capital during this sample period have 0.0051 significantly lower expected returns than all other firms during this sample period when Florida increased the enforceability of non-competition agreements. This suggests that these firms had a decrease in risk relative to other firms who had lower levels of organization capital when Florida made it easier to enforce non-compete clauses, and therefore made it more difficult for employees to exercise their outside options.

These results provide additional evidence that changes in workers abilities to exercise their outside option and take their NPV positive to another firm can affect the riskiness of firms who have higher levels of these types of employees.

### 3.6 Robustness Tests

In this section I show that the main results of the paper are robust to a variety of alternative measures of the HHI, the asset pricing model used to calculate unconditional portfolio alphas, and different sorts on organization capital and HHI. Table 30 shows the results of these tests. In panels 1 and 2, I still form dual-sort quintile portfolios, but the HHI is calculated using other common firm characteristics. Specifically, in Panel 1 (2), the HHI is calculated using total assets (market value of equity) instead of sales. The results are qualitatively similar: High competition excess returns are 5.785 (5.374) and are still significant at the 1% level in comparison to the original result of 6.188. The low competition excess returns are 2.762 (0.962) and still insignificant in comparison to the original result of 1.202. High competition alphas are 6.455 (5.816) and are still significant at the 1% level in comparison to the original result of 6.792, and low competition alphas are 2.959 (1.580) and still insignificant in comparison to the original result of 1.629.

In panel 3 I still form dual-sort quintile portfolios, but I use the Fama-French 4 factor model to calculate unconditional portfolio alphas. In this case, the high competition alpha is 5.357 and is still significant at the 5% level and the low competition alpha is 1.284 and still insignificant. Each of these are qualitatively similar to the original point estimates.

In panel 4 I now form dual-sort quartile portfolios, and I use the original market model to calculate unconditional portfolio alphas. In this case, high competition excess returns are 6.178 and still significant at the 1% level, and low competition excess returns are 2.056 and still insignificant. The high competition portfolio alpha is 7.248 and still significant at the 1% level, and the low competition alpha is 2.604 and still insignificant. Each of these are still qualitatively similar to the original point estimates. Other combinations of quantile splits have similar results.

These robustness tests show that the main results hold using a variety of alternative computational techniques. In fact, amongst the robustness tests shown here, the sign and level of significance remains the same for the main results of interest. This provides compelling evidence that the main results are valid.

## 3.7 Conclusion

Organization capital is risky for firms due to key employees being able to exercise their outside option and take their postive net present value ideas to a competing firm. However, this risk should only be prevalent when these opportunities are available. One way to measure these opportunities is through the degree of product market competition. Firms with high organization capital in more competitive industries should have higher exposure to this risk than similar firms in more concentrated industries because key employees have more opportunities to exercise their outside options due to the greater availabilty of competing jobs. I double-sort firms on the degree of product market competition and level of organization capital and find that average returns are only significantly higher in the most competitive industries versus the most concentrated industries. The spread portfolio in the most competitive industries has average returns of 6.2% per year (t-stat of 2.89) and positive annual alpha of 6.79% (t-stat of 3.10), whereas the spread portfolio in the least competitive industries has positive but insignificant average returns of 1.2% per year (t-stat of 0.69) and positive but insignificant alpha of 1.63% per year (t-stat of 0.87).

If competition is driving the main result, then as the level of competition changes over time, the risk for firms with high organization capital should change as well. As competition decreases, high organization capital firms should become less risky since the ability of key employees to excercise their outside option decreases. I show that the time series of the aggregate HHI is related to the risk of high organization capital firms in the highest quintile of HHI: an increase in competition is positively and significantly correllated with conditional alphas for firms with high levels of organization capital in the highest quintile of HHI.

Finally, I use a different proxy for the abiliity of firms to exercise their outside option: the enforceability of non-competition agreements. As enforceability of these contracts decrease, it is easier to exercise outside options, which is riskier for firms with high levels of organization capital. I show that when Texas decreased enforceability of these contracts, expected returns significantly increased, and when Florida increased enforceability, expected returns significantly decreased. These results suggest that firms with high organization capital are riskier only when their key employees can viably exercise their outside option and extract economic rents from existing shareholders.

**Table 25**
Descriptive Statistics

| | Organization capital quintiles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Competition quintiles | Average of annual number of firms | | | | | Average of annual averages of firm size | | | | |
| Low | 60.4 | 61.8 | 63.5 | 71.7 | 73.4 | 3309.8 | 2292.5 | 3487.4 | 2681.0 | 1187.5 |
| 2 | 66.5 | 64.2 | 65.5 | 69.7 | 68.8 | 3957.2 | 3700.9 | 1502.7 | 1874.7 | 1507.7 |
| 3 | 65.6 | 67.3 | 67.9 | 68.3 | 62.6 | 2736.4 | 2186.0 | 2149.9 | 1200.4 | 463.5 |
| 4 | 63.5 | 63.9 | 70.5 | 66.5 | 62.7 | 1956.6 | 2895.7 | 2008.7 | 1456.5 | 499.6 |
| High | 61.3 | 72.6 | 75.8 | 73.1 | 68.2 | 1679.2 | 3916.3 | 3036.5 | 2575.6 | 617.7 |
| | Average of organization capital | | | | | Average of HHI | | | | |
| Low | 0.35 | 0.78 | 1.19 | 1.74 | 3.32 | 0.867 | 0.861 | 0.863 | 0.865 | 0.866 |
| 2 | 0.34 | 0.73 | 1.11 | 1.65 | 3.37 | 0.554 | 0.548 | 0.557 | 0.554 | 0.556 |
| 3 | 0.35 | 0.73 | 1.13 | 1.68 | 3.55 | 0.386 | 0.387 | 0.385 | 0.385 | 0.386 |
| 4 | 0.33 | 0.72 | 1.11 | 1.69 | 3.66 | 0.261 | 0.259 | 0.259 | 0.259 | 0.259 |
| High | 0.27 | 0.59 | 0.95 | 1.44 | 3.27 | 0.132 | 0.132 | 0.130 | 0.127 | 0.130 |

**Table 26**
Asset pricing tests for spread portfolios from 25 dual-sorted portfolios on organization capital and product market competition. "OMK" is a replication of Table IV of Eisfeldt and Papanikolaou (2013). "High (Low) Competition" is a spread portfolio of high minus low organization capital for the lowest (highest) quintile of product market competition as measured by the HHI. Portfolios are rebalanced in June of every year, and the sample period is from 1963 - 2019. The data were pulled from CRSP and Compustat beginning in 1950. Panel A reports the average excess returns over the risk-free rate $E[R] - r_f$. Panel B reports portfolio CAPM alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio.

| Portfolio | OMK | High Competition | Low Competition |
|---|---|---|---|
| | Panel A: Portfolio moments | | |
| E{R]-rf (%) | 3.007** | 6.188*** | 1.202 |
| | (2.32) | (-2.885) | (-0.686) |
| Observations | 678 | 678 | 678 |
| R2 | 0.008 | 0.011 | 0.001 |
| | Panel B: CAPM | | |
| B MKT | -1.636** | -1.116 | -0.789 |
| | (-2.66) | (-1.454) | (-0.855) |
| A (%) | 3.892** | 6.792*** | 1.629 |
| | (1.316) | (3.103) | (0.874) |
| Observations | 678 | 678 | 678 |
| R2 | 0.048 | 0.007 | 0.005 |

**Table 27**

Asset pricing tests for 25 dual-sorted portfolios on organization capital and product market competition. Portfolios are rebalanced in June of every year, and the sample period is from 1963 - 2019. The data were pulled from CRSP and Compustat beginning in 1950. Panel A reports the average excess returns over the risk-free rate $E[R]-r_f$. Panel B reports portfolio CAPM alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio.

| | Organization capital quintiles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| Competition quintiles | Average excess returns | | | | | t-statistics of average excess returns | | | | |
| Low | 6.594 | 6.828 | 6.793 | 8.077 | 7.797 | 2.652 | 2.678 | 2.644 | 8.077 | 3.405 |
| 2 | 5.579 | 4.157 | 7.719 | 8.511 | 8.299 | 2.368 | 1.513 | 2.880 | 3.367 | 3.607 |
| 3 | 6.785 | 6.207 | 8.193 | 8.366 | 8.745 | 2.473 | 2.323 | 3.472 | 2.784 | 3.647 |
| 4 | 6.181 | 6.345 | 5.082 | 7.973 | 7.587 | 2.152 | 2.591 | 1.904 | 3.553 | 2.626 |
| High | 2.974 | 6.214 | 6.665 | 7.644 | 9.163 | 0.978 | 2.698 | 3.157 | 3.663 | 3.474 |
| | Portfolio alphas | | | | | t-statistics of portfolio alphas | | | | |
| Low | -0.322 | -0.285 | 0.563 | 2.609 | 1.307 | -0.258 | -0.247 | 0.332 | 1.737 | 1.047 |
| 2 | -0.737 | -2.687 | 0.589 | 1.764 | 2.443 | -0.593 | -1.810 | 0.419 | 1.174 | 1.651 |
| 3 | -1.131 | -1.339 | 0.978 | 1.247 | 1.899 | -0.764 | -0.977 | 0.783 | 0.734 | 1.129 |
| 4 | -1.337 | -1.339 | -2.055 | 1.395 | -0.034 | -0.966 | -0.487 | -1.822 | 1.068 | -0.023 |
| High | -4.153 | -0.020 | 1.175 | 2.264 | 2.639 | -1.965 | -0.019 | 0.836 | 1.802 | 1.447 |

**Table 28**
Regressions of annualized conditional alphas for high and low HHI quintiles on annual average HHI

| | $\alpha^H$ | $\alpha^L$ |
|---|---|---|
| HHI (inverted) | 145.04*** | -92.17*** |
| | (5.04) | (-4.70) |
| Intercept | 64.28*** | -34.66*** |
| | (5.59) | (-4.43) |
| Observations | 47 | 47 |
| adj Rˆ2 | 0.35 | 0.31 |

**Table 29**
Triple difference regressions of high organization capital firms located in states that have changed the enforceability of their non-compete laws. The dependent variable of interest is expected returns calculated using the Fama French 3 factor model. Firm monthly betas are calculated using a market model from rolling regressions of the past 60 months ensuring that at least 20 months of data are available. The sample period is from Garmaise 2011: 1992 - 2004.

| Panel A: FF3F model | | | |
|---|---|---|---|
| | Texas | Louisiana | Florida |
| Post | n/a | n/a | n/a |
| | | | |
| Treatment: state | 0.0028*** | -0.0005 | 0.0023** |
| | (2.91) | (-0.27) | (2.23) |
| Treatment: high organization capital | 0.0053*** | 0.0002 | 0.0053*** |
| | (10.67) | (0.77) | (14.65) |
| Post X treat_state | -0.0027*** | -0.0056 | -0.0024* |
| | (-2.59) | (-1.30) | (-1.93) |
| Post X treat_orgcap | -0.0055*** | 0.0027*** | -0.0019*** |
| | (-10.16) | (5.13) | (-4.41) |
| Treat_state X treat_orgcap | -0.0044*** | 0.0011 | 0.0050*** |
| | (-2.82) | (0.37) | (3.09) |
| Triple difference | 0.0043** | 0.006 | -0.0051*** |
| | (2.47) | (0.74) | (-2.60) |
| Year/month fixed effects | Yes | Yes | Yes |
| R-square | 0.414 | 0.414 | 0.396 |
| No. of observations | 536,148 | 536,148 | 536,148 |

**Table 30**

Robustness tests using a variety of alternate measures of HHI, asset pricing model, and quantile portfolio sorts.

| Panel 1: HHI: Scaled by assets | | |
|---|---|---|
| Panel A1: Portfolio moments | High Competition | Low Competition |
| $E[R] - r_f$ (%) | 5.785*** | 2.762 |
| | (2.87) | (1.47) |
| Observations | 678 | 678 |
| R2 | 0.010 | 0.000 |
| Panel B1: CAPM | | |
| $\beta_{MKT}$ | -1.238* | -0.365 |
| | (-1.67) | (-0.39) |
| $\alpha$ (%) | 6.455*** | 2.959 |
| | (3.11) | (1.49) |
| Observations | 678 | 678 |
| R2 | 0.009 | 0.001 |

| Panel 2: HHI: Scaled by market equity | | |
|---|---|---|
| Panel A2: Portfolio moments | High Competition | Low Competition |
| $E[R] - r_f$(%) | 5.374*** | 0.962 |
| | (2.61) | (0.53) |
| Observations | 678 | 678 |
| R2 | 0.009 | 0.000 |
| Panel B2: CAPM | | |
| $\beta_{MKT}$ | -0.817 | -1.142 |
| | (-1.07) | (-1.40) |
| $\alpha$ (%) | 5.816*** | 1.580 |
| | (2.78) | (0.83) |
| Observations | 678 | 678 |
| R2 | 0.004 | 0.016 |

| Panel 3: 4-Factor model | | |
|---|---|---|
| Panel A3: Portfolio moments | High Competition | Low Competition |
| $E[R] - r_f$(%) | 6.188*** | 1.202 |
| | (2.88) | (0.69) |
| Observations | 678 | 678 |
| R2 | 0.011 | 0.001 |
| Panel B3: 4-Factor model | | |
| $\beta_{MKT}$ | -0.768 | -1.180 |
| | (-1.00) | (-1.53) |
| $\beta_{SMB}$ | -0.194 | 1.270 |
| | (-0.11) | (1.60) |
| $\beta_{HML}$ | 0.404 | -1.992* |
| | (0.30) | (-1.73) |
| $\beta_{MOM}$ | 1.789** | 1.463 |
| | (2.03) | (1.61) |
| $\alpha$ (%) | 5.357** | 1.284 |
| | (2.33) | (0.82) |
| Observations | 678 | 678 |
| R2 | 0.037 | 0.050 |

| Panel 4: 4x4 dual sorts | | |
|---|---|---|
| Panel A4: Portfolio moments | High Competition | Low Competition |
| $E[R] - r_f$ (%) | 6.178*** | 2.056 |
| | (3.58) | (1.21) |
| Observations | 678 | 678 |
| R2 | 0.015 | 0.002 |
| Panel B4: CAPM | | |
| $\beta_{MKT}$ | -1.976*** | -1.014 |
| | (-2.98) | (-1.01) |
| $\alpha$ (%) | 7.248*** | 2.604 |
| | (4.09) | (1.41) |
| Observations | 678 | 678 |
| R2 | 0.045 | 0.012 |

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