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When Bankers Go to Hail: Insights into Fed–Bank Interactions from Taxi Data

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Abstract. We introduce taxi ridership between the Federal Reserve (Fed) Bank of New York and large financial institutions headquartered in New York City as a novel proxy for Fed–bank face-to-face interactions. We document a negative relation between past Fed–bank interactions and future stock market returns, particularly on days around the Fed's public announcements. We also find significantly elevated Fed–bank interactions immediately following the lifting of the Federal Open Market Committee blackout. Our findings suggest that the Fed increases its information gathering via face-to-face interactions when it possesses negative private information about the condition of the economy.

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1. Introduction

Although the Federal Reserve System has become more transparent in recent decades (Bernanke 2010), outside observers have limited visibility into the activities of these critically important financial institutions. A long literature has sought to explain how the Federal Reserve (Fed) sets and implements monetary policy under uncertainty, but little is publicly known about the private channels through which the Fed and commercial financial institutions learn from each other.

We fill this void by developing a novel proxy for face-to-face interactions between Fed and bank employees and examine how changes in the level of such meetings relate to future stock market returns. Our evidence suggests that when the Fed or banks possess negative private information about the condition of the economy that has not yet been reflected in market prices, they are more likely to meet face-to-face.

To measure Fed–bank face-to-face interactions, we use taxi data from the New York City (NYC) Taxi and Limousine Commission (TLC, the Commission). We pinpoint taxi pickup and drop-off locations through latitude and longitude coordinates and match these coordinates with the street addresses of the Federal Reserve Bank of New York (FRBNY) and other financial institutions.[1] We then aggregate cab ridership between the FRBNY and these banks to obtain a measure of Fed–bank interactions, which several tests indicate captures the movements of bankers and FRBNY employees.

Consistent with the Fed's gathering of more information when it possesses negative private information about the condition of the economy, we find that increases in levels of Fed–bank ridership are negatively related to future market returns in the subsequent 10 days. This relation is statistically significant over our 2009–2014 sample period, but is most negative during the financial crisis and surrounding the Fed's public announcements. A one standard deviation increase in our measure of Fed–bank interactions is associated with a decrease in the expected daily excess return of the stock market of 19.1 ($t = 3.11$) basis points (bps) around the Fed's Federal Open Market Committee (FOMC) announcements and its testimony before the U.S. Congress. Given that we find no significant relation between Fed–bank ridership and pre-event market returns, these findings suggest that most of the information driving these interactions is not impounded into market prices until it is publicly revealed around Fed announcements.[2]

We also examine the nature of Fed–bank face-to-face interactions over the FOMC cycle, particularly during the blackout period when there is a restriction on the flow of monetary policy-related information from the Fed to banks. We find a significant increase in Fed–bank interactions immediately following the lifting of the blackout period. Rides from the major commercial banks to the New York Fed significantly increase almost immediately after the midnight lifting of a communications blackout imposed on Federal Reserve staff. We also find that Fed–bank interactions are significantly elevated prior to announcements of initiations and expansions of quantitative easing (QE): the days before such an announcement have 37.4% more Fed–bank interactions than average. Finally, lunchtime meetings away from the New York Fed and major commercial banks are elevated beginning shortly before the FOMC announcement and ending a week afterward.

Our paper contributes to the literature on the impacts of Fed activity on stock returns. In addition to Lucca and Moench (2015) and Cieślak et al. (2019), there is a large recent literature examining stock return patterns throughout the FOMC cycle. Neuhierl and Weber (2018) provide evidence that the pre-FOMC drift documented by Lucca and Moench (2015) extends as far as 25 days prior to FOMC announcements, although Neuhierl and Weber (2018) exclude the most recent years from their sample because of consistently near-zero federal funds rates. Neuhierl and Weber (2016, p. 3) examine weekly changes in one- and three-month Fed funds futures to construct a "slope factor" that signals changes in monetary policy. They document that a positive slope factor signals faster than expected monetary policy tightening and is negatively related to future weekly returns. Bernile et al. (2016) find evidence of informed trading during embargoes of FOMC scheduled announcements.[3]

In a contemporaneous paper, Morse and Vissing-Jørgensen (2020) use Federal Reserve governors' calendars from 2007 to 2018 to examine how Fed information reaches stock markets. They link the high returns during even weeks around FOMC meetings presented by Cieślak et al. (2019) to interactions between Federal Reserve governors and Federal Reserve Bank presidents. Although the calendars provide detailed insights into the top echelons of the Federal Reserve System, they are limited to a small group's formal activities. With data capturing the activities of a larger set of Fed insiders, we present evidence that interactions between presumably lower-level Fed employees and large banks also lead the market. In contrast to Morse and Vissing-Jørgensen (2020), we find that these interactions predict negative market returns in the coming weeks.

Our study also relates to a recent strand of literature that uses aspects of the transportation and travel industries to answer finance-related questions. For instance, Koudijs (2016) examines drivers of 18th-century stock-price movements using data on ships that conveyed news. Yermack (2014) and Lee et al. (2018) employ movements of corporate jets to study business connections. Two contemporaneous working papers contribute to this literature using New York City taxi data to study information flow within the financial sector (Choy and Hope 2021, Cicero et al. 2022).[4]

2. Measuring Fed–Bank Interactions

2.1. Data, Bank Office Locations, and General Methodology

The New York City Taxi and Limousine Commission has released over a billion yellow taxi trip records back to 2009. We restrict attention to yellow taxi rides because all of the financial institutions we examine are located in a region where only yellow taxis can provide hail service.[5] Throughout our sample period, our data include each trip's pickup and drop-off times, pickup and drop-off coordinates, distance, passenger count, fare, tip, and manner of payment. Although the TLC does not guarantee the completeness and accuracy of the ride data, it audits its ride records and has the authority to take steps to ensure adequate reporting (NYC Taxi and Limousine Commission 2017).[6]

We generally employ a daily sample that runs from January 2009 through December 2014, where each day is defined as 5:00 a.m. through 4:59 a.m. the following day. The year 2014 saw a large increase in the use of rideshare apps by businesses and the first public release of the taxi data under New York State's Freedom of Information Law (Saitto 2014, Whong 2014, Rao 2015, White 2015). Significant patterns in rides may reflect the movements of small sets of individuals, and substitution by any of them away from taxis due to changes in business practice or due to concerns about privacy could result in a significant loss of signal.[7] Moreover, Citi and Bank of New York (BNY) Mellon both relocated their headquarters in 2015, so we chose to end our sample in December 2014. In unreported analyses, we find that the negative relations between past Fed–bank ridership levels and future stock market returns are qualitatively similar when we extend the sample until June 2016 (after which period granular pickup and drop-off data are no longer available) and incorporate the changes in locations for Citi and BNY Mellon using our best guesses for the move dates.

To create our measure of Fed–bank interactions, we must first define the primary locations for the New York Fed and the other financial institutions in our sample. The New York Fed's headquarters at 33 Liberty Street occupies its entire block, and the New York Fed has staff at 33 Maiden Lane across the street to the east (Federal Reserve Bank of New York 2023). Because the main entrance to 33 Maiden Lane is directly across from 33 Liberty Street, we focus on rides in the vicinity of 33 Liberty.

To identify rides as interactions between New York Fed employees and commercial bankers, we focus on large financial institutions with which New York Fed staff would be expected to interact with professionally. We define this set as the U.S.-based subset of the Financial Stability Board's (2014) Global Systemically Important Banks (G-SIBs). We consider only important front-office presences, defined as locations that are both listed as properties in 10-K filings and serve as corporate, investment-banking, financial-market, or asset-management headquarters. We employ nine locations where Bank of America, BNY Mellon, Citigroup, Goldman Sachs, JPMorgan Chase and Morgan Stanley have offices during our sample period.[8] All of the banks except for BNY Mellon are also primary dealers and are consequently expected to provide the New York Fed with market commentary (Federal Reserve Bank of New York 2010). We report the addresses of the institutions in our sample in Table A.3 in the online appendix.

We generally define Fed–bank interactions based on the number of cab rides with one end point in (or nearby) the New York Fed's census block and the other endpoint in (or nearby) a commercial bank's census block. Census block boundaries are provided by the New York City Department of City Planning, and census blocks largely correspond to city blocks. Where a building or a complex of interest is the only substantial development on its census block, we consider pickups and drop-offs mapped to that block; otherwise, we restrict attention to the slice of the block that it occupies. Because of the scatter that we observe around roads and the possibility that relevant pickups and drop-offs occur across from buildings, we use expanded versions of census blocks or slices thereof.[9]

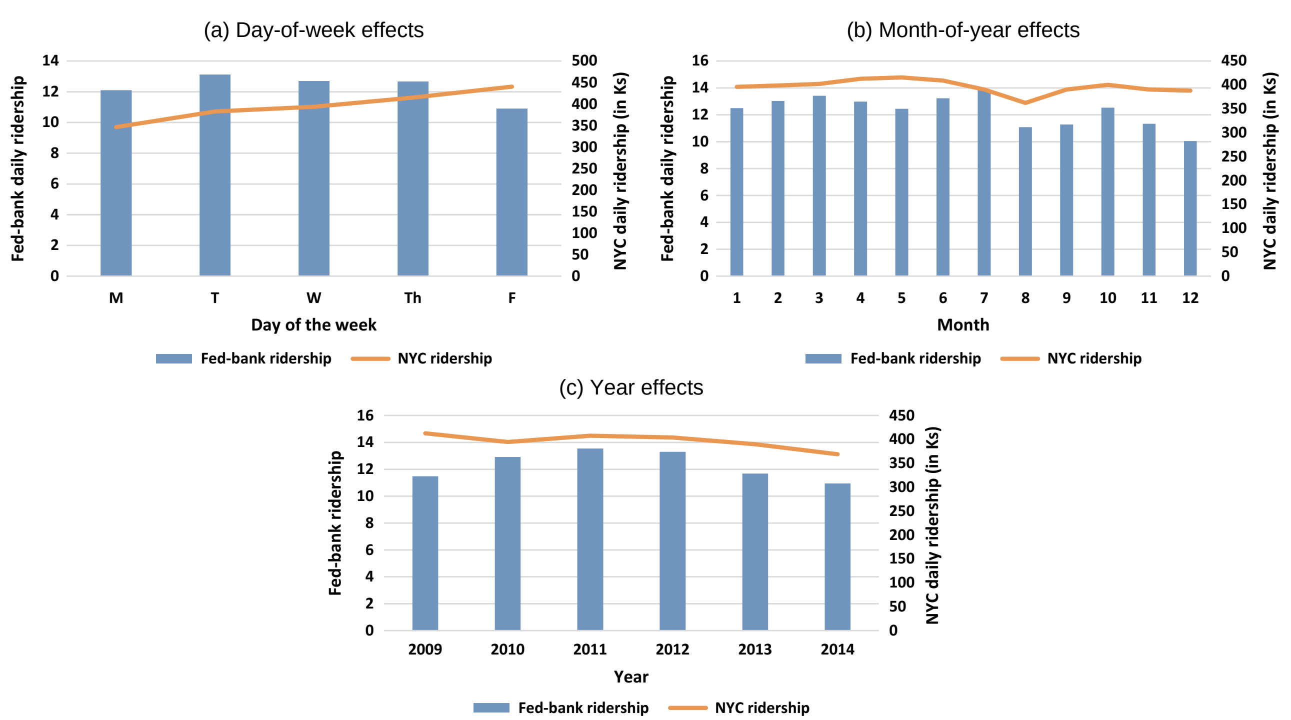
The average number of rides between the Fed and one of the banks in our sample (henceforth, "Fed–bank ridership" or "Fed–bank interactions") on trading days is 12.31 ($\sigma = 4.39$). The average daily yellow cab ridership within Manhattan on trading days is 396,151 ($\sigma = 51,880$). Both of these ridership measures vary by the day of the week, the month of the year, and the year, as shown in Figure 1.

Fed–bank ridership is at its highest on Tuesdays (13.1) and its lowest on Fridays (10.9), whereas yellow cab ridership within Manhattan is at its peak on Fridays (440,352) and its lowest on Mondays (346,327). Fed–bank ridership is at its highest (lowest) level in July (December), at 13.9 (10.0) rides per trading day, whereas yellow cab ridership within Manhattan is at its highest (lowest) level in May (August), at 415,523 (362,316) rides per trading day. Finally, there are also year effects, as 2014 has the lowest Fed–bank ridership and total Manhattan ridership, at 11.0 and 368,832, respectively. When these ridership levels are regressed onto day-of-week, month-of-year, or year fixed effects, the F-statistics are highly significant and range from 8.4 to 198.4. Because of this variation in taxi ridership, we control for day-of-week, month-of-year, and year effects when analyzing Fed–bank interactions.

2.2. Validating Our Measure of Fed–Bank Interactions

We conduct several tests to validate that the ride data capture the movements of bankers and New York Fed

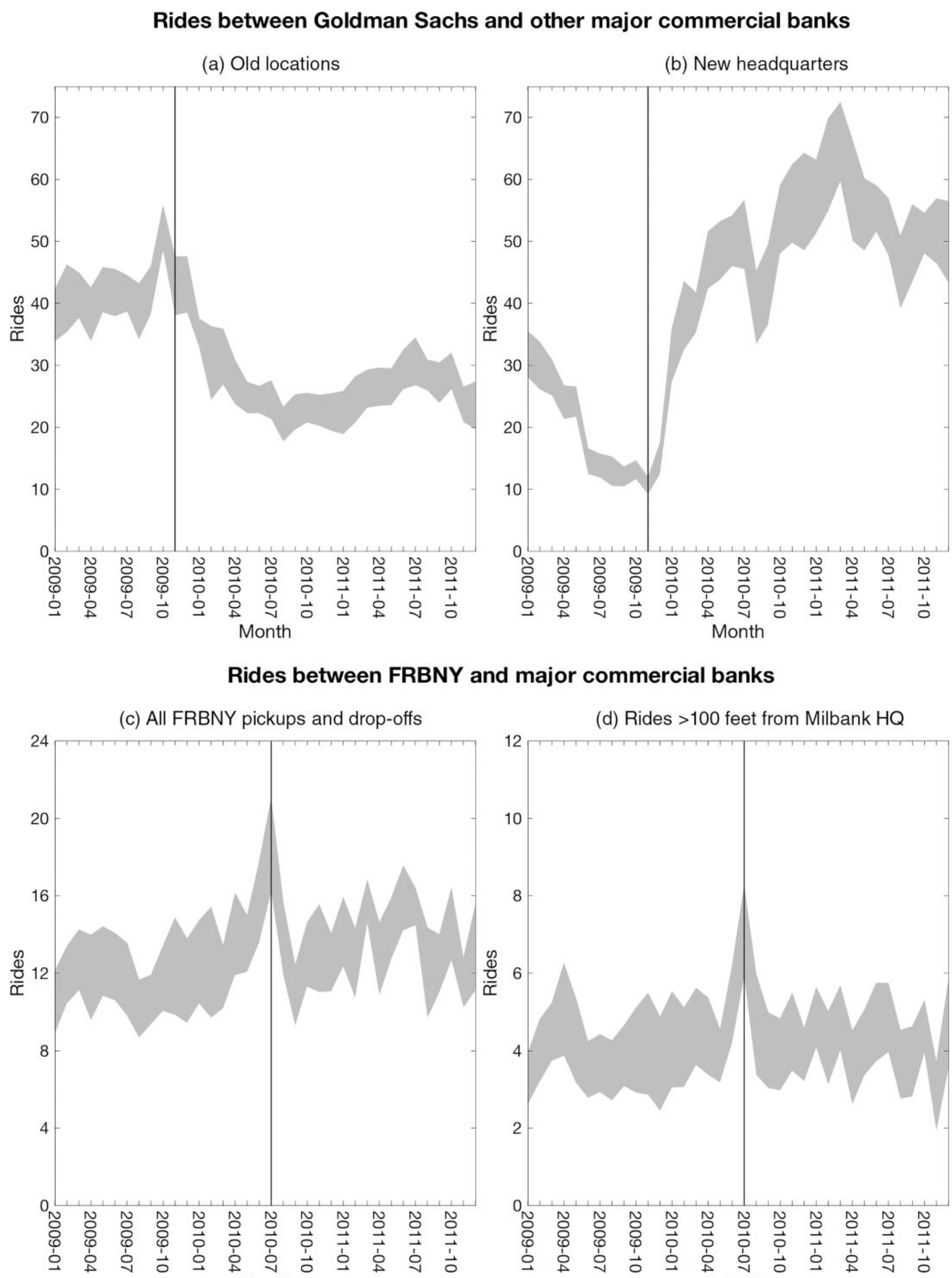
Figure 1. (Color online) Average Daily Ridership by Weekday, Month, and Year



Notes. We report the average daily yellow cab ridership within Manhattan and between the Fed and the banks in our sample. In panel (a), we report the averages by the day of the week. In panel (b), we plot the averages by month of the year. In panel (c), we plot the averages by year. Taxi ridership comes from the NYC Taxi and Limousine Commission.

employees. We begin by examining whether taxi rides reflect the movement of business activity resulting from the relocation of Goldman Sachs's headquarters and trading floor from 85 Broad Street and One New York Plaza to 200 West Street (Carney 2009, Craig 2010). Figure 2(a) and (b), presents two-standard-deviation confidence bands for monthly means of weekday ride volumes between Goldman Sachs's old locations and new

Figure 2. Two-Standard-Deviation Confidence Bands Around Monthly Means of Weekday Ride Volumes Between Major Financial Institutions



Notes. The vertical bars in panels (a) and (b) indicate the commencement of Goldman Sachs's staff relocation by November 2009. The vertical bars in panels (c) and (d) mark the signing of Dodd–Frank into law in July 2010. A day spans the period from 5:00 a.m. to 4:59 a.m. the next morning. The taxi data are from the NYC Taxi and Limousine Commission.

headquarters and the buildings of the other major banks. The decline in the old locations' volume and the increase in the new headquarters' volume are strikingly coincident and begin around November 2009, approximately when the first staff began working at 200 West Street (Craig 2010). The confidence bands after mid-2010 generally do not overlap with any of those before November 2009, which suggests that we can identify the movement of bank employees using taxi data.

To assess whether the taxi data capture the conduct of FRBNY business, we examine ride volumes around milestones in the passage of the Dodd–Frank Wall Street Reform and Consumer Protection Act (Dodd–Frank). Dodd–Frank represents the greatest overhaul of American financial regulation in decades, and one would expect that preparations for its possible passage would increase interactions among FRBNY staff at its main locations, the institutions that the Federal Reserve System regulates, and the Fed staff embedded in those institutions (Paletta and Lucchetti 2010). We examine ride volumes on, before, and after the dates listed in the U.S. Congress's overview of actions on Dodd–Frank, excluding the long list of dates on which only conference committees were held.[10] We find that from the filing of the conference report onward, the day before each milestone is in the top 99.4% of days by ride volume (Table 1, panel A). The day before the Senate agreed to the conference report and the day before President Obama signed the bill into law saw the two highest volumes of the whole sample. High ride volumes are not limited to those days: Figure 2(c) presents two-standard-deviation confidence bands around the monthly means of weekday ride volumes, and overall ride volumes in June and July 2010 are exceptionally high.[11]

3. Understanding Fed–Bank Interactions

3.1. Testable Predictions

In 1977, Congress amended the Federal Reserve Act, directing the FOMC to "maintain long run growth of the monetary and credit aggregates commensurate with the economy's long run potential to increase production, so as to promote effectively the goals of maximum employment, stable prices and moderate long-term interest rates."[12] To achieve this mandate, the Fed collects information about the state of the economy, and a working assumption throughout this paper is that some of this information is collected via face-to-face interactions between employees of the New York Fed and the important non-Fed financial institutions located in New York City.

To develop predictions about the relation between the Fed's information gathering and the stock market returns around its subsequent public announcements, we must specify the relation between the Fed's information gathering and their level of optimism and uncertainty about the state of the economy. We expect the Fed's demand for additional information to be stronger when it is unclear what its optimal policy response is. This is likely to occur when the Fed does not have a good understanding of the underlying state of the economy. During our sample period, we also expect this to have occurred when the Fed received negative private information about the state of the economy. The reason for this is that short-term interest rates were effectively zero, so the typical policy action for stimulating the economy (cutting interest rates) was not

Table 1. Quantiles and Counts of Daily Rides Between the New York Fed and Major Commercial Banks Around Dodd–Frank Milestones

Dodd–Frank milestone	Date	$t-1$	t	$t+1$
Panel A. All direct rides—quantile (count)				
Introduced in House	December 2, 2009	86.9 (17)	3.3 (5)	68.5 (14)
Passed in House	December 11, 2009	16.6 (8)	81.9 (16)	60.6 (13)
Passed with amendment in Senate	May 20, 2010	68.5 (14)	33.3 (10)	51.6 (12)
Conference report filed	June 29, 2010	99.4 (24)	99.8 (27)	60.6 (13)
Conference report agreed in House	June 30, 2010	99.8 (27)	60.6 (13)	51.6 (12)
Conference report agreed in Senate	July 15, 2010	100.0 (32)	75.9 (15)	96.4 (20)
Signed by president	July 21, 2010	99.9 (29)	96.4 (20)	86.9 (17)
Panel B. Pickups and drop-offs >100 feet from Milbank HQ—quantile (count)				
Introduced in House	December 2, 2009	93.9 (7)	2.7 (0)	88.4 (6)
Passed in House	December 11, 2009	26.6 (2)	77.5 (5)	10.4 (1)
Passed with amendment in Senate	May 20, 2010	44.4 (3)	26.6 (2)	44.4 (3)
Conference report filed	June 29, 2010	97.2 (8)	98.8 (9)	26.6 (2)
Conference report agreed in House	June 30, 2010	98.8 (9)	26.6 (2)	44.4 (3)
Conference report agreed in Senate	July 15, 2010	100.0 (12)	88.4 (6)	97.2 (8)
Signed by president	July 21, 2010	93.9 (7)	93.9 (7)	62.9 (4)

Notes. Quantiles as percentages are presented first and then counts in parentheses. The milestones are the events in the passage of Dodd–Frank listed in U.S. Congress (2023) with the exception of conference committees. In column headings, t indicates the date of the event, and $t-1$ and $t+1$ are respectively the previous weekday and the subsequent weekday. For greater consistency with workdays, daily ride volume is calculated as the count of rides from 5:00 a.m. through 4:59 a.m. The quantiles are calculated over the 1,425 weekdays in the filtered sample spanning 2009 through 2014. The taxi data are from the NYC Taxi and Limousine Commission. HQ, Headquarters.

an option because of the zero lower bound.[13] We provide some evidence supporting these assumptions in Section A.3 of the online appendix, where we analyze economic projections from the Fed Board of Governors and Fed bank presidents.

Given these assumptions, there should be a negative relation between the amount of additional information that the Fed chooses to acquire and the market returns around Fed announcements, because high past levels of information acquisition suggest that the Fed is either pessimistic or uncertain about the condition of the economy. To the extent that the Fed has private information that has not been priced into the market, the stock market will fall when uncertainty or pessimism increases around Fed announcements.

See Section A.1 of the online appendix for a formal model that develops the ideas described above. The discussion above leads to the following prediction.

Prediction 1. *Past Fed–bank interactions and future stock market returns are negatively correlated, especially around Fed announcements.*

Empirically, we can observe Fed–bank interactions using the taxi ridership data. To the extent that the Fed chooses to interact more with financial institutions when it seeks to acquire more information about the state of the economy, these Fed–bank interactions are a proxy for the amount of additional private information that the Fed collects. We can also observe the market's reaction to the Fed's public announcements.

3.2. Empirical Relation Between Fed–Bank Interactions and Market Returns

To empirically test Prediction 1, we employ a measure of abnormal Fed–bank interactions on a given trading day, t. Because most of the Fed's information gathering presumably takes place during working hours, we focus on ridership between 9:00 a.m. and 4:00 p.m. to minimize measurement error. Recall from Figure 1 that the level of taxi cab ridership varies across the day of the week, the month of the year (because of seasonality), and the year (because of long-term time trends in ridership). Thus, to obtain a measure of abnormal Fed–bank interactions each day, we consider the residuals from a simple regression where the daily level of rides between the Fed and commercial banks is regressed onto day-of-the-week indicators, month-of-the-year indicators, and year indicators. Specifically, we define $RidershipResidual_t$ as the residual (ε_t) from the regression

$$\text{Ridership}_t = \alpha + \gamma_{\text{day of the week}_t} + \gamma_{\text{month of the year}_t} + \gamma_{\text{year}_t} + \varepsilon_t. \quad (1)$$

Our measure of the relative intensity of the Fed's recent information gathering activity is derived from the evolution of $RidershipResidual_t$ over the prior month. Specifically, let $AvgResidual_{[t-j,t-k]}$ be defined as the average daily *RidershipResidual* between days $t-j$ and $t-k$, inclusive, and let $\Delta Rides_t$ be defined as $AvgResidual_{[t-10,t-1]} - AvgResidual_{[t-20,t-11]}$. For ease of interpretation, we normalize $\Delta Rides$ to have zero mean and unit standard deviation. We then consider the sample of all trading days with sufficient past observations to estimate $\Delta Rides$, and we regress the daily excess returns of the stock market (in bps) onto $\Delta Rides$. We report the results of this regression in column (1) of Table 2.

The coefficient of $\Delta Rides$ is -6.35 ($t = 2.19$), so a one standard deviation increase in $\Delta Rides$ is associated with a decrease in the daily expected excess return of the market of 6.35 bps.[14] This magnitude (6.35 bps) is roughly comparable to the constant (7.79 bps), so when $\Delta Rides$ is one standard deviation above its mean, the expected excess return of the market is roughly zero.

Having established that rising levels of Fed–bank interactions are followed by unusually low stock market returns, we next examine the timing of the stock market return predictability: Is the predictability most pronounced around public announcements, or during periods when the Fed is quiet? In addition to their FOMC announcements, Fed officials also communicate to the public when they appear before the U.S. Congress to testify about their views on the economy and their monetary policy plans. For example, the chair of the Fed appears before Congress to deliver a semiannual Monetary Policy Report. Moreover, the chair will periodically appear before Congress to testify about the economic outlook.[15]

We define the indicator *Fed event* to take the value one if the day is within a trading day (i.e., event day -1, 0, or $+1$) of an FOMC announcement or Fed congressional testimony, and zero otherwise. Over our sample period, approximately 29% of trading days are Fed event days. We also define the indicator *No Fed event* as $1 - \textit{Fed event}$. In column (2) of Table 2, we interact $\Delta Rides$ with *Fed event* and *No Fed event*. Here, we see that the negative relation between past Fed–bank interactions and future market returns is concentrated around Fed events: The coefficient of $\Delta Rides \times \textit{Fed event}$ is -19.13 ($t = 3.11$), whereas the coefficient of $\Delta Rides \times \textit{No Fed event}$ is just -1.63 ($t = 0.50$). Thus, a one standard deviation increase in $\Delta Rides$ is associated with a decrease in the daily return of the market around Fed events by 19.13 bps.

In columns (3) and (4) of Table 2, we separately consider FOMC announcements and the Fed's congressional testimony, respectively: in column (3), *Fed event* is defined as being within a trading day of an FOMC announcement, and in column (4), it is defined as being within a trading day of Fed testimony before Congress. Using both of these indicators of Fed events, we continue to see a statistically significant negative relation between past Fed–bank interactions and market returns. The magnitude of the effect is similar around FOMC and congressional speech events.

Table 2. Relation Between Current Market Returns and Past Fed–Bank Interactions

	(1)	(2)	(3)	(4)	(5)
$\Delta Rides$	−6.35**				
	(−2.19)				
Fed event		9.21	−2.14	13.75*	7.78
		(1.27)	(−0.18)	(1.70)	(1.04)
$\Delta Rides \times$ *Fed event*		−19.13***	−19.42**	−20.90***	−15.26**
		(−3.11)	(−2.11)	(−2.77)	(−2.14)
$\Delta Rides \times$ *No Fed event*		−1.63	−4.69	−2.77	3.34
		(−0.50)	(−1.54)	(−0.89)	(0.62)
$Fedevent_{t+3}$					−8.71
					(−1.26)
$Fedevent_{t+6}$					−2.11
					(−0.31)
$Fedevent_{t-3}$					1.76
					(0.25)
$Fedevent_{t-6}$					0.53
					(0.08)
$\Delta Rides \times Fedevent_{t+3}$					1.18
					(0.18)
$\Delta Rides \times Fedevent_{t+6}$					−3.55
					(−0.58)
$\Delta Rides \times Fedevent_{t-3}$					−10.26
					(−1.47)
$\Delta Rides \times Fedevent_{t-6}$					−4.18
					(−0.62)
Constant	7.79***	5.15	8.30***	4.42	8.37
	(2.60)	(1.58)	(2.70)	(1.37)	(1.55)
Observations	1,490	1,490	1,490	1,490	1,484
R^2	0.00	0.01	0.00	0.01	0.01
Fed event type		Any	FOMC	Testimony	Any

Notes. The sample consists of trading days, and the dependent variable is the excess return (in bps) of the stock market on the given day. The term $\Delta Rides$ is a normalized measure of the change in Fed–bank interactions over the prior month. Specifically, we first regress daily Fed–bank ridership between 9:00 a.m. and 4:00 p.m. onto day of week, month of year, and year fixed effects. We interpret the residual on day t as a measure of the abnormal Fed–bank interactions for that day. The term $\Delta Rides$ is defined as $AvgResidual_{[t-10,t-1]} - AvgResidual_{[t-20,t-11]}$, where $AvgResidual_{[t-j,t-k]}$ is the average daily residual between days $t-j$ and $t-k$. The term $\Delta Rides$ is then normalized to have zero mean and unit standard deviation. The term *Fed event* is an indicator variable taking the value one if the given trading day is within one trading day of a public announcement or Fed testimony before Congress. Specifically, *Fed event* takes the value one for either type of public address in columns (2) and (5); in column (3) (4), it takes the value one only if it is within a trading day of an FOMC announcement (Fed congressional testimony). The term $Fed\,event_{t-j}$ is defined the same as *Fed event*, except it indicates whether trading day $t-j$ is within a trading day of a Fed event as opposed to trading day t. We report t-statistics computed using White standard errors in parentheses. The taxi data are from the NYC Taxi and Limousine Commission, and excess returns of the stock market are taken from Ken French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

*, **, *** denotes statistical significance at the 10, 5, and 1 percent levels, respectively.

In column (5), we assess whether the information gets impounded before the public announcements/testimony, or it gets fully impounded at the time of the announcements/testimony, or it is slowly impounded into stock market valuations. Specifically, we define indicator variables $Fed\,event_{t+j}$ taking the value one on trading day t if (and only if) trading day $t+j$ is within one trading day of an FOMC announcement or a Fed congressional testimony. We also interact these variables with $\Delta Rides$. If the private information embedded in $\Delta Rides$ gets revealed prior to public events, we should see significant coefficients on the interactions for $j > 0$. Conversely, if it takes several days for the information to get impounded into market valuations, we should see significant coefficients on the interactions for $j < 0$. We define these variables for $j \in \{-6, -3, +3, +6\}$. We find that the coefficient of $\Delta Rides \times Fedevent$ remains economically and statistically significant at -15.26 ($t = 2.14$), and that none of the other interactions are statistically significant. Among these other interaction variables, the coefficient of $\Delta Rides \times Fedevent_{t-3}$ is the largest (in absolute value) and has the largest t-statistic: -10.26 ($t = 1.47$). Thus, there is some weak evidence that the private information embedded in the Fed–bank interactions is not immediately impounded into market valuations, but, rather, takes a few days to be fully incorporated into market valuations.

We next examine which years are the most important contributors for our findings in Table 2 and whether our

Table 3. Relation Between Current Market Returns and Past Fed–Bank Interactions, by Year

	2009	2010	2011	2012	2013	2014
Panel A. Estimations within each year						
Fed event	10.86	28.81*	−24.54	18.11	−0.78	22.34*
	(0.47)	(1.71)	(−1.24)	(1.47)	(−0.06)	(1.95)
Δ*Rides* × *Fed event*	−71.24***	−8.23	−20.70	8.31	−17.41	−13.66
	(−2.99)	(−0.72)	(−1.52)	(0.68)	(−1.18)	(−1.46)
Δ*Rides* × *No Fed event*	−13.14	−3.97	6.86	1.45	−4.52	−3.95
	(−0.83)	(−0.57)	(0.55)	(0.24)	(−0.84)	(−0.77)
Constant	10.50	−1.71	10.08	1.40	12.85***	−0.72
	(0.90)	(−0.20)	(0.84)	(0.24)	(2.75)	(−0.14)
Observations	232	252	252	250	252	252
R^2	0.05	0.02	0.01	0.01	0.01	0.03
Panel B. Excluding each year						
Fed event	7.03	5.32	17.60**	7.28	11.28	6.81
	(1.01)	(0.67)	(2.30)	(0.88)	(1.38)	(0.83)
Δ*Rides* × *Fed event*	−10.41*	−22.75***	−18.43***	−24.19***	−19.22***	−20.19***
	(−1.84)	(−3.16)	(−2.68)	(−3.51)	(−2.93)	(−2.81)
Δ*Rides* × *No Fed event*	−0.84	−1.05	−3.36	−2.49	−1.06	−1.14
	(−0.25)	(−0.28)	(−1.09)	(−0.65)	(−0.28)	(−0.30)
Constant	4.45	6.52*	4.14	5.97	3.39	6.45*
	(1.35)	(1.84)	(1.30)	(1.59)	(0.88)	(1.69)
Observations	1,258	1,238	1,238	1,240	1,238	1,238
R^2	0.00	0.01	0.01	0.01	0.01	0.01

Notes. We reproduce column (2) of Table 2. In panel A, we reproduce the regression within each year, and in panel B, we reproduce it by excluding each year.
*, **, *** denotes statistical significance at the 10, 5, and 1 percent levels, respectively.

results are completely driven by a single year. In Table 3, we estimate the regression in column (2) of Table 2 within each year (panel A) and excluding each year (panel B). We find that the coefficient of Δ*Rides* × *Fed event* has the largest magnitude in 2009 ($\beta = -71.24$, $t = 2.99$), but that it remains significant at the 10% level when 2009 is excluded from the sample ($\beta = -10.41$, $t = 1.84$).

3.3. Alternative Explanations for the Stock Market Return Patterns

3.3.1. Private Signals or Monetary-Policy Posture? We have assumed that the stock market's response around Fed announcements is linked to the Fed's private information about the underlying state of the economy: When the Fed has received positive or precise private signals, the market reacts positively, and when the Fed has received negative or imprecise signals, the market reacts negatively. According to our story, it is this association that drives the relation between Fed–bank ridership and the returns around Fed announcements.

An alternative explanation is that the returns around Fed announcements are driven by the market's updating of its views about the Fed's monetary policy plans. More specifically, because the market generally reacts positively (negatively) to expansionary (contractionary) monetary policy surprises, it is possible that the Fed simply interacts more with financial institutions prior to announcements of contractionary monetary policy.

This alternative story has a clear cross-sectional prediction: If we sort stocks based on their performance around expansionary monetary policy surprises and we consider the portfolio that goes long (short) the stocks that perform best (worst) following expansionary monetary policy surprises, then we should find a negative association between past Fed–bank interactions and the performance of the portfolio. To test this prediction, we use the monetary policy exposure (MPE) index developed by Ozdagli and Velikov (2020) to sort stocks into quintiles based on their performance around expansionary monetary policy surprises. In columns (1)–(5) of Table 4, we repeat the regression from column (2) of Table 2, except we use each of the five MPE portfolio returns as our dependent variable. We find that the coefficient of Δ*Rides* × *Fedevent* increases almost monotonically from MPE portfolio 1 (−22.66) to MPE portfolio 5 (−16.76). Importantly, the coefficient is negative and highly significant in all quintiles, which is consistent with the results being driven by market-level information being released, not specific Fed actions being announced.

In column (6) of Table 4, we use the cross-sectional difference in returns between quintile 5 and quintile 1 as our dependent variable. The coefficient of Δ*Rides* × *Fedevent* in this regression, 5.90, is statistically significant at the 10% level ($t = 1.66$). Although the t-statistic is just barely statistically significant at the 10% level, the sign is the opposite of the alternative prediction, and this result

Table 4. Portfolio Returns and Changes in Ridership—Cross-Sectional Analysis

	(1) MPE1	(2) MPE2	(3) MPE3	(4) MPE4	(5) MPE5	(6) MPE5–MPE1
Fed event	9.08	10.65	11.25	6.09	7.52	−1.56
	(0.98)	(1.22)	(1.46)	(0.89)	(1.19)	(−0.36)
Δ*Rides* × *Fed event*	−22.66***	−21.22***	−21.47***	−17.95***	−16.76***	5.90*
	(−2.89)	(−2.86)	(−3.25)	(−3.11)	(−3.08)	(1.66)
Δ*Rides* × *No Fed event*	−2.09	−1.92	−2.25	−1.70	−1.44	0.65
	(−0.49)	(−0.47)	(−0.63)	(−0.55)	(−0.49)	(0.33)
Constant	8.38**	7.35*	6.58*	6.83**	4.67	−3.71*
	(1.97)	(1.81)	(1.87)	(2.20)	(1.61)	(−1.79)
Observations	1,490	1,490	1,490	1,490	1,490	1,490
R^2	0.01	0.01	0.01	0.01	0.01	0.00

Notes. The sample consists of trading days. In column (1), the dependent variable is the return (in bps) of the lowest MPE portfolio, that is, the portfolio of stocks that respond least positively in response to expansionary monetary policy surprises (Ozdagli and Velikov 2020). Columns (2)–(5) report the results for the MPE portfolio numbers 2–5, where the higher the MPE portfolio, the more positively the stocks respond to expansionary monetary policy surprises. In column (6), the dependent variable is the difference in the return of MPE portfolio 5 and MPE portfolio 1. Terms Δ*Rides* and *Fed event* are defined in the Table 2 notes. We report *t*-statistics computed using White standard errors in parentheses. The taxi data are from the New York City Taxi and Limousine Commission, and excess returns of the stock market are taken from Ken French's website.

*, **, *** denotes statistical significance at the 10, 5, and 1 percent levels, respectively.

is thus inconsistent with the idea that high levels of Fed–bank interactions are simply proxying for future contractionary monetary policy surprises.

Although the results reported in Table 4 are inconsistent with the alternative explanation, they are congruous with our story that high levels of Fed–bank interactions are associated with the Fed's possession of negative private information about the condition of the economy. Thus, Fed–bank interactions should act as a proxy for the Fed's propensity to engage in expansionary (not contractionary) monetary policy, so the performance of the long–short portfolio should be positively associated with past Fed–bank interactions, which is what we see in the data.

Though these findings are more consistent with our story than the alternative, there are a few caveats. First, the statistical significance is weak at 10%. Second, interest rates were basically flat because of the binding zero lower bound throughout our sample period. Although Ozdagli and Velikov (2020, p. 321) argue that their index successfully captures stocks' responses to monetary policy in the post-2008 period, their baseline analysis focuses on the pre-2008 period. Thus, although the evidence is more consistent with our story than the alternative, we cannot completely rule out the possibility that ridership proxies for the Fed's monetary policy decisions rather than its private information about the underlying condition of the economy.

3.3.2. Public Rather Than Private Fed Signal? Thus far, we have assumed that the amount of additional information that the Fed collects is driven by its private information rather than investors' beliefs about the economy. However, it is plausible that the Fed's demand for additional information is also driven by the general public level of bearishness or uncertainty in the market rather than its own (private) bearishness or uncertainty about the condition of the economy. If its information gathering is primarily driven by public information, there should be an association between the Fed's information gathering and *past* stock market returns. Specifically, increases in the general level of uncertainty or pessimism about the economy should be associated with declines in market valuations, so we should see a negative association between past stock market returns and current levels of Fed–bank interactions.

Our measure of abnormal Fed–bank interactions on day t is $RidershipResidual_t$, that is, the residual from (1). Our measure of past stock market returns is the cumulative excess return on the market between trading days $t-j$ and $t-1$ for various horizons, j. In Table 5, we report the results for one-day, one-week, two-week, three-week, one-month, six-week, one-quarter, and two-quarter horizons.

We find negative coefficients at the one-week, six-week, one-quarter, and two-quarter horizons, and positive coefficients at the one-day, two-week, three-week, and one-month horizons. However, none of the eight coefficients are statistically significant at the 10% level, with the largest *t*-statistic being 1.44 (the positive coefficient at the 2-week horizon).

Overall, we find little evidence that Fed–bank interactions are driven by general, market-wide levels of uncertainty. Rather, the evidence is more supportive of our assumption that it is the Fed's own private information that drives the level of Fed–bank interactions.

4. Fed–Bank Interactions and the FOMC Blackout Period

During the blackout period around FOMC meetings, Federal Reserve staff are not permitted to discuss monetary policy and economic matters that have not already been cleared and widely disseminated (Federal Reserve Board

Table 5. Relation Between Current Fed–Bank Interactions and Past Market Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ret_{[-1,-1]}$	0.02 (0.40)							
$Ret_{[-5,-1]}$		−0.01 (−0.21)						
$Ret_{[-10,-1]}$			0.03 (1.44)					
$Ret_{[-15,-1]}$				0.02 (1.24)				
$Ret_{[-20,-1]}$					0.01 (0.61)			
$Ret_{[-30,-1]}$						−0.00 (−0.33)		
$Ret_{[-63,-1]}$							−0.00 (−0.16)	
$Ret_{[-125,-1]}$								−0.00 (−0.88)
Constant	4.48	4.48	4.46	4.46	4.47	4.49	4.48	4.51
Observations	1,510	1,510	1,510	1,510	1,510	1,510	1,510	1,510
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes. The sample consists of trading days, and the dependent variable is the number of Fed–bank ridership between 9:00 a.m. and 4:00 p.m. The term $Ret_{[-j,-k]}$ denotes the cumulative percent excess return of the stock market between trading days $t-j$ and $t-k$, inclusive, that is, the event "$Ret_{[-j,-k]} = 1$" corresponds to the cumulative excess return between $t-j$ and $t-k$ equaling 1%. We report t-statistics computed using White standard errors in parentheses. The taxi data are from the New York City Taxi and Limousine Commission, and excess returns of the stock market are taken from Ken French's website.

of Governors 2014). Over the sample employed in this paper, the blackout period began a week before the FOMC meeting's first day—typically eight days before the announcement—and ended a day after the announcement of policy decisions (Federal Reserve Board of Governors 2014). Revisions to Federal Reserve policies implemented in 2017 further restricted permissible communication between Federal Reserve insiders and outside parties around FOMC meetings (Federal Reserve Board of Governors 2017).

We expect the Fed to collect less information during the blackout period because of the costs of compliance with strict rules, the potential appearance of impropriety, and the possibility of inadvertant violations of guidelines. Because there is no reason to expect a sharp decline in the Fed's or banks' demand for information right at the end of the blackout period, we predict an increase in the level of Fed–bank interactions immediately following the lifting of the blackout period.

Prediction 2. *There is an increase in Fed–bank interactions immediately following the lifting of the blackout.*

We test Prediction 2 in Sections 4.1 and 4.2 using daily and intraday ridership data, respectively.

4.1. Daily Ridership over the FOMC Cycle

Consider the following regression:

$$\text{Ridership}_t = \alpha + \sum_{s=-2}^{+2} \beta_s FOMC_{event\ day\ +s} + \gamma_{\text{day of week}_t} + \gamma_{\text{month of year}_t} + \gamma_{\text{year}_t} + \varepsilon_t, \qquad (2)$$

where $FOMC_{event\ day\ +s}$ is the indicator variable that day t is exactly s trading days after an FOMC announcement;[16] that is, we regress daily ridership between the Fed and the banks in our sample onto five indicator variables representing the five trading days centered around the FOMC announcement as well as fixed effects for the day of the week, month of the year, and year to control for weekday effects, seasonalities, and long-run time trends in taxi cab ridership, respectively.

Because the blackout period ends at 11:59 p.m. on the day after the announcement (i.e., event day +1), we predict there to be a significant increase in Fed–bank interactions two days after the FOMC announcement, that is, on event day +2. We report the results of the regression in column (1) of Table 6. Even though it is during the blackout period, we find significantly elevated Fed–bank interactions on the day before and after the FOMC announcement: There are an additional 1.18 (1.29) Fed–bank interactions on the day before (after) the FOMC announcement, which is statistically significant ($t = 1.98$ and 2.21, respectively).

The pent-up demand for additional information from the Fed (or banks) should be greatest following FOMC meetings where the Fed implements novel forms of monetary policy because there should be more uncertainty following such actions. During our sample period, the Fed issued announcements regarding four rounds of its large-scale asset purchase (LSAP) program: "QE1," "QE2," "QE3," and "Operation Twist." There are 14

Table 6. Ridership Around FOMC Meetings

	(1)	(2)	(3)
$FOMC_{event\ day\ -2}$	0.96	1.25*	1.25*
	(1.58)	(1.88)	(1.87)
$FOMC_{event\ day\ -1}$	1.18**	0.50	0.50
	(1.98)	(0.69)	(0.68)
$FOMC_{event\ day\ 0}$	0.28	0.38	0.38
	(0.47)	(0.56)	(0.56)
$FOMC_{event\ day+1}$	1.29**	1.79***	1.79**
	(2.21)	(2.58)	(2.58)
$FOMC_{event\ day\ +2}$	0.42	−0.33	−0.32
	(0.80)	(−0.56)	(−0.55)
$FOMC_{event\ day\ -2} \times LSAP$		−1.03	−0.09
		(−0.79)	(−0.07)
$FOMC_{event\ day\ -1} \times LSAP$		2.32**	1.32
		(2.34)	(1.23)
$FOMC_{event\ day\ 0} \times LSAP$		−0.32	0.21
		(−0.27)	(0.13)
$FOMC_{event\ day\ +1} \times LSAP$		−1.77	−2.40*
		(−1.60)	(−1.84)
$FOMC_{event\ day\ +2} \times LSAP$		2.57**	2.90**
		(2.55)	(2.30)
$FOMC_{event\ day\ -2} \times LSAP \times LSAPexpansion$			−2.63
			(−0.98)
$FOMC_{event\ day\ -1} \times LSAP \times LSAPexpansion$			2.79**
			(2.51)
$FOMC_{event\ day\ 0} \times LSAP \times LSAPexpansion$			−1.46
			(−0.89)
$FOMC_{event\ day\ +1} \times LSAP \times LSAPexpansion$			1.76
			(1.04)
$FOMC_{event\ day\ +2} \times LSAP \times LSAPexpansion$			−0.91
			(−0.57)
Constant	12.18	12.18	12.18
Observations	1,510	1,510	1,510
R^2	0.15	0.15	0.16

Notes. We regress daily ridership between the Fed and the banks in our sample onto variables indicating the FOMC event time (in trading days). The variable $FOMC_{event\ day\ -x}$ ($FOMC_{event\ day\ +x}$) is the indicator that the given date is exactly x trading days before (after) an FOMC announcement. The variable *LSAP* indicates that the given FOMC meeting is one of the 14 where the FOMC issued an announcement regarding its large scale asset purchase program, and *LSAPexpansion* indicates that the given FOMC meeting was one where the FOMC announced an initiation or expansion to the program. We provide descriptions of each of the Fed's 14 LSAP announcements in Table A.2 in the online appendix, and in panel A of Table 7, we specify which dates we classified as expansions. The sample consists of all trading days between 2009 and 2014. Each regression includes fixed effects for the day of the week (Monday–Friday), the month of the year (January–December), and year (2009–2014). Windows beginning during the span from 12:00 a.m. through 4:00 a.m. are treated as part of the preceding calendar day. We report *t*-statistics computed using White standard errors in parentheses. The taxi data are from the NYC Taxi and Limousine Commission.

*, **, *** denotes statistical significance at the 10, 5, and 1 percent levels, respectively.

FOMC meetings during our sample period with LSAP announcements regarding these four rounds of quantitative easing.[17] We define the indicator variable *LSAP* to take a value of one for the trading days that are within two trading days (i.e., event days −2 through +2) of an LSAP announcement. In column (2) of Table 6, we include interactions of this indicator with the FOMC event day indicators from column (1). Here, we see that our prediction of elevated Fed–bank interactions immediately following the blackout period is confirmed: Relative to the FOMC meetings where there is not an LSAP announcement, there are an additional 2.57 (t = 2.55) Fed–bank interactions following the end of the blackout period of an FOMC meeting with an LSAP announcement. Inspecting the interactions on the day immediately before and after the announcement, we see that the elevated interactions on the day following the announcement were driven by the FOMC meetings where there is not an LSAP announcement. In contrast, the elevated interactions on the day prior to the FOMC meetings are driven by the meetings where there is an announcement regarding the Fed's LSAP program ($\beta = 2.32$, $t = 2.34$).

We further explore the interactions around LSAP announcements by assessing the content of the FOMC's announcement. Presumably, the most significant LSAP announcements are the ones where the FOMC announces an initiation of a new round of quantitative easing and/or an expansion of the current round. We classify 5 of the 14 announcements as meeting this criterion.[18] We define the indicator variable *LSAPexpansion* to take a value of one for the trading days that are within two trading days (i.e., event days −2 through +2) of an LSAP announcement of an initiation and/or expansion of a round of quantitative easing. In column (3) of Table 6, we add interactions of this variable with the FOMC event time indicators to the regression from column (2). Surprisingly, there are fewer Fed–bank interactions following the lifting of the blackout around announcements of expansions to the program relative to other LSAP announcements ($\beta = -0.91$), although this difference is insignificant ($t = 0.57$). However, the FOMC's announcements of an initiation/expansion of its LSAP program are associated with significantly elevated Fed–bank interactions on the day immediately before the announcement: there are an extra 2.79 (t = 2.51) Fed–bank interactions on the day before an LSAP expansion announcement relative to the other LSAP announcements, and even the other LSAP announcements are associated with elevated Fed–bank interactions relative to other FOMC announcements ($\beta = 1.32$), although that difference is not statistically significant (t = 1.23). Compared with a typical Tuesday (and controlling for month of year and year effects), there are an extra 4.61 Fed–bank rides on the day prior to an LSAP announcement, which is 37.4% of the average daily Fed–bank rides (12.31).[19] In summary, the increased Fed–bank interactions immediately before FOMC announcements are especially pronounced prior to the days the FOMC announces a new round of quantitative easing or an expansion to the current round of QE.

With a total of 14 LSAP announcements, we can analyze the preannouncement Fed–bank ridership levels separately

Table 7. Abnormal Intraday Ridership Prior to Announcements of Expansions to a Large-Scale Asset Purchase Program

Date	Time window						
	5:00 a.m.–9:00 a.m.	9:00 a.m.–1:00 p.m.	1:00 p.m.–5:00 p.m.	5:00 p.m.–9:00 p.m.	9:00 p.m.–1:00 a.m.	1:00 a.m.–5:00 a.m.	Sum across all windows
Panel A. Expansions/initiations of the program							
March 17, 2009	−0.99	0.97	0.06	1.84	0.16	−0.34	1.71
November 2, 2010	2.77	1.05	2.01	−0.61	1.35	−0.36	6.21
September 20, 2011	−0.59	−0.21	0.90	2.27	−0.27	0.62	2.72
September 12, 2012	−1.63	2.50	−1.05	0.49	2.67	1.33	4.30
December 11, 2012	0.29	2.37	1.80	−0.48	−1.31	−0.54	2.14
Mean across all rows	−0.03	1.34	0.74	0.70	0.52	0.14	3.41
Panel B. Contractions/endings of the program							
August 11, 2009	2.88	0.49	0.46	−1.04	0.48	−0.31	2.95
September 22, 2009	0.69	3.25	−0.51	−1.84	0.51	−0.29	1.81
November 3, 2009	4.16	−2.15	−1.52	1.25	0.23	−0.31	1.66
December 17, 2013	−2.32	0.56	0.08	0.52	0.06	−0.16	−1.24
September 16, 2014	2.17	0.11	−1.87	0.46	−1.24	−0.33	−0.70
October 28, 2014	−0.25	−2.27	−0.97	−0.75	0.63	−0.50	−4.11
Mean across all rows	1.22	0.00	−0.72	−0.23	0.11	−0.32	0.06
Panel C. Other announcements							
August 9, 2010	2.64	−0.75	0.34	0.93	−1.36	0.71	2.50
June 21, 2011	2.86	0.57	−0.41	−0.04	−0.69	1.49	3.78
June 19, 2012	−0.20	−2.58	0.50	0.11	2.03	−0.81	−0.95
Mean across all rows	1.77	−0.92	0.14	0.33	−0.01	0.46	1.78

Notes. We divide each trading day into six four-hour intervals. For each time interval, we take the sample of all trading days and regress the number of rides in the given intraday interval onto day of week (Monday–Friday) fixed effects, month of year (January–December) fixed effects, year (2009–2014) fixed effects, and indicators for whether the given date is FOMC event day −2, −1, 0, +1, +2, or other. We then report the residuals from these regressions for each of the time windows and each of the days immediately prior to one of the 14 FOMC announcements regarding its large-scale asset purchase programs. The taxi data are from the NYC Taxi and Limousine Commission.

for each one. To examine the abnormal ridership by day and time, we divide each trading day into six four-hour intervals. Recall that we map rides that occur between midnight and 5:00 a.m. to the previous day, so each day effectively begins at 5:00 a.m., leaving us with the intervals 5:00–9:00 a.m., 9:00 a.m.–1:00 p.m., etc. For each of these intervals, we restrict the sample to rides during those hours, and we consider the sample of all trading days. We then run the regression specified by (2) separately for each of the six four-hour intervals. We report the residuals for each (day, time window) in Table 7. Panel A (B) reports the residuals for the LSAP expansion (contraction) announcements, and panel C considers the others.[20]

In the first column, we list the date, and in the second column, we report the residual from the 5:00 a.m.–9:00 a.m. regression. The other columns are analogous. In panel A, we see that Fed–bank interactions were especially elevated (residual = 6.21) prior to the November 3, 2010, FOMC announcement, when the Fed announced QE2. However, this observation does not drive the finding, as Fed–bank interactions are elevated on the day before each of the 5 LSAP expansion announcements. Regarding the intraday windows, we see that on the days prior to LSAP expansion announcements, Fed–bank interactions are most elevated during normal work hours (9:00 a.m.–5:00 p.m.).

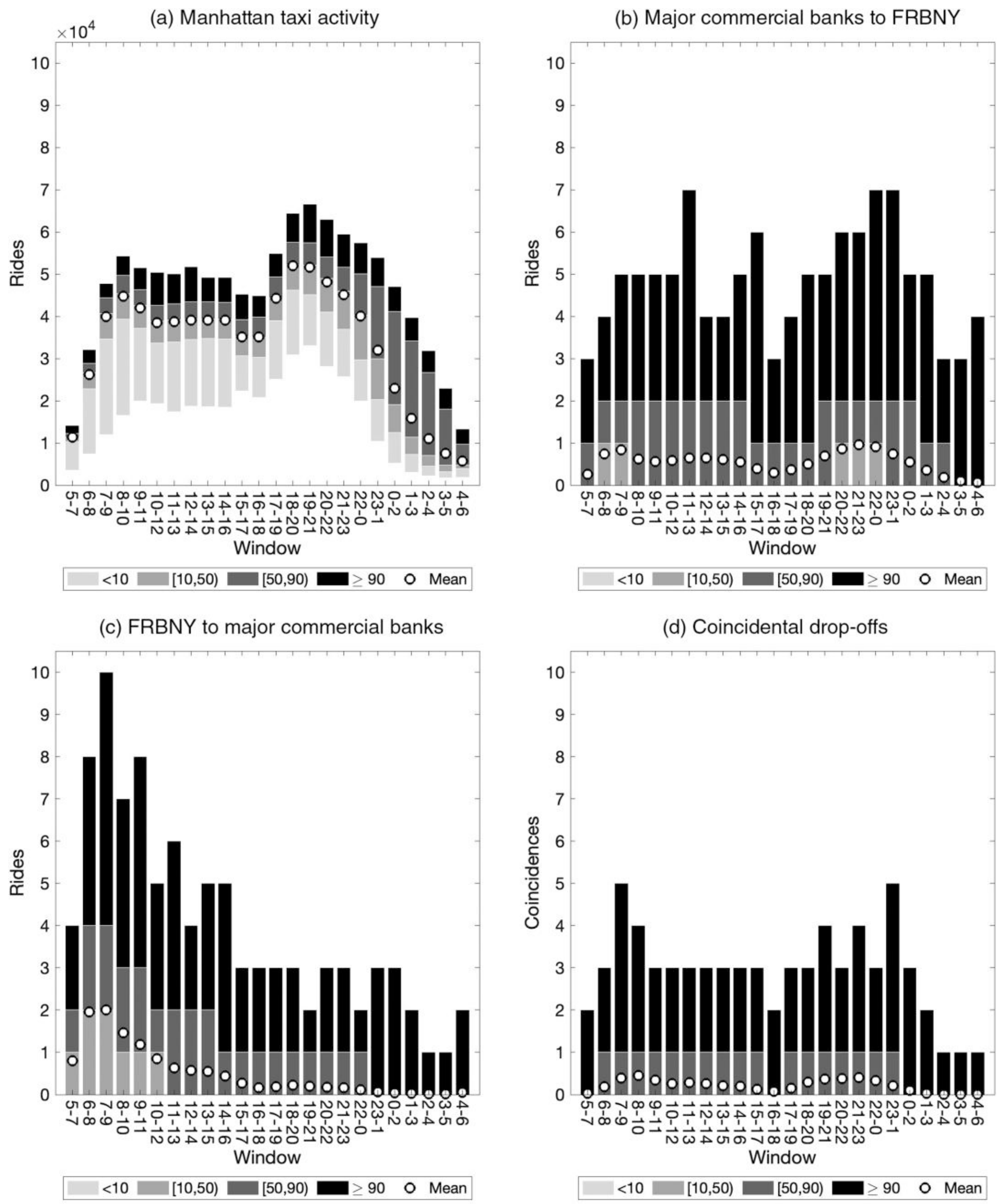
In panel B, we see that Fed–bank interactions are not elevated on the day before contractions to the LSAP programs, and in panel C, we see that they are moderately elevated on the day prior to other LSAP announcements.

4.2. Intraday Ridership Around the Blackout Period

We next examine intraday patterns in ridership. Figure 3 presents summary statistics for aggregate Manhattan taxi activity: the mean of pickup and drop-off volumes for intra-Manhattan rides, and for rides between the New York Fed and the major commercial banks. Panel (a) shows that aggregate Manhattan activity reaches a nadir between 4:00 a.m. and 5:00 a.m., and our activity-based definition of a day is the span from 5:00 a.m. through 4:59 a.m. the following day.[21] Panels (b) and (c) indicate that trips between the New York Fed and the major commercial banks are not frequent, with no median count over two using bihourly windows. Intraday ride volumes from the FRBNY's vicinity to those of the major commercial banks and vice versa are generally positively skewed.

We map a calendar day to an event day by obtaining the offset in calendar days from the nearest FOMC announcement, with a negative integer indicating a day prior to the announcement and a positive integer indicating a day subsequent to the announcement.[22] We employ two- and three-hour spans that begin at the top of an hour, mapping by drop-off time.[23]

Figure 3. Means and Quantiles of Counts of Weekday Rides and Coincidental Drop-Offs



Notes. The sample spans 1,425 weekdays from the beginning of 2009 through the end of 2014. For greater consistency with a typical workday, an intraday window starting during the span from 12:00 a.m. up to and including 4:00 a.m. is mapped to the previous calendar day. Panel (a) shows the mean of bihourly pickup and drop-off volumes of intra-Manhattan yellow taxi rides. Panel (b) shows the bihourly volumes of yellow taxi rides from the sample of locations where major commercial banks have substantial front-office presences to the FRBNY. Panel (c) shows the bihourly volumes of yellow taxi rides from the FRBNY to the sample of locations where major commercial banks have substantial front-office presences. Panel (d) shows the bihourly volumes of coincidental drop-offs of passengers picked up around the FRBNY and passengers picked up around locations where major commercial banks have substantial front-office presences. The taxi data are from the NYC Taxi and Limousine Commission.

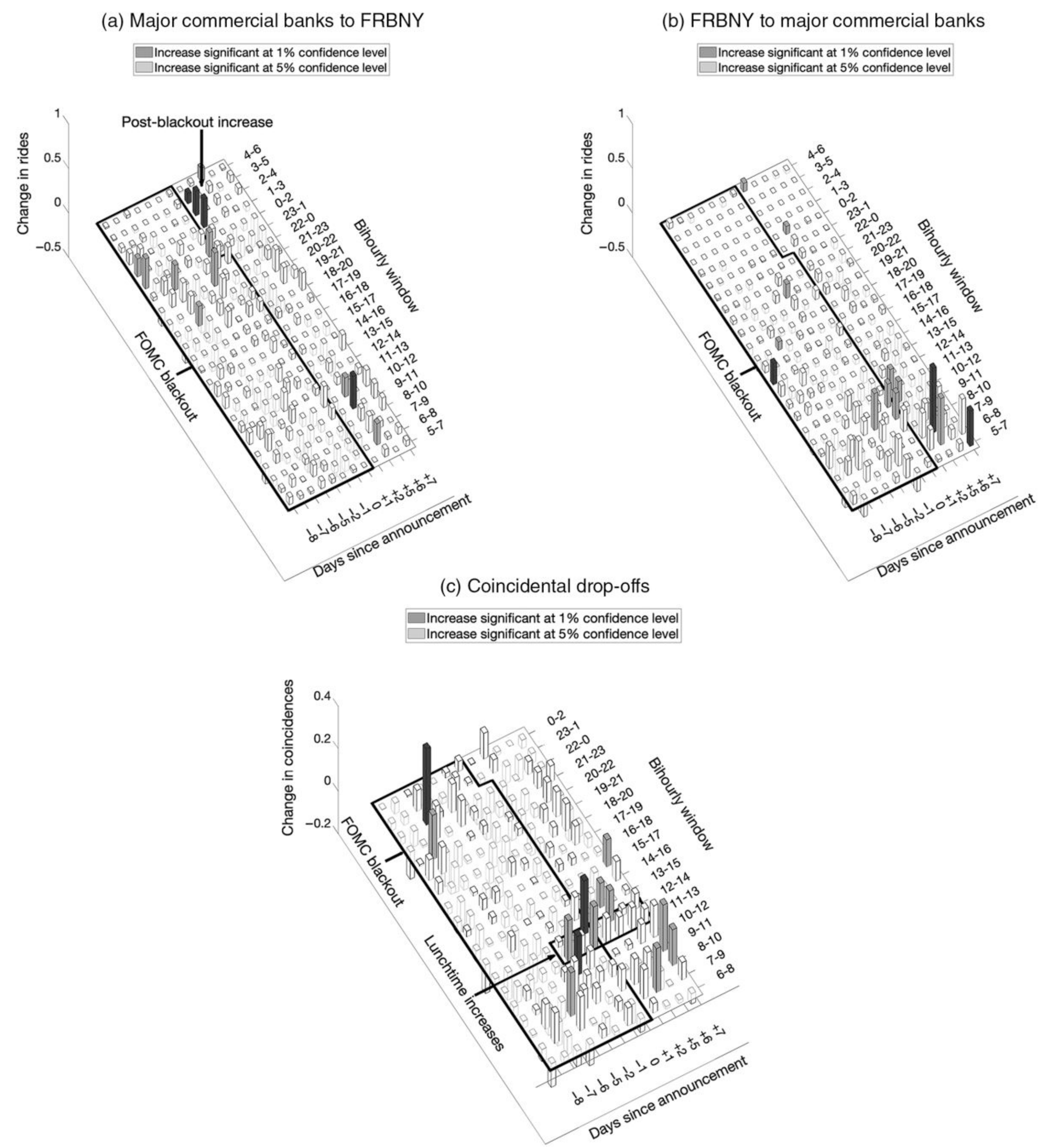
Given that the intraday ride counts are discrete, nonnegative, and often small, we employ Poisson regressions.[24] The prototypical regression for rides during intraday window f employs a conditional mean, or intensity, λ_t^f, of the following form:

$$\lambda_t^f = exp\left(\iota_t\beta_\iota + z_t^f\gamma + \alpha_{ym(t)} + \theta_{wd(t)}\right), \tag{3}$$

where t indexes the date, ι_t is an indicator of whether date t falls in the FOMC window, z_t^f is aggregate Manhattan taxi activity during window f on date t, α_{ym} is a fixed effect for year-month ym, and θ_{wd} is a weekday effect. The period controls soak up intraweek cyclicality and lower-frequency seasonality and trends, whereas the inclusion of z_t^f addresses the possibility that some FOMC windows may coincide with relatively high or low Manhattan ride volume unrelated to Fed activities. Using M-estimation, we cluster at the year-month level to accommodate arbitrary heteroskedasticity and within-month serial correlation. Our null hypothesis for each FOMC window is a nonpositive change, and our alternative is a positive change.[25]

4.2.1. Intraday Changes in Direct Rides Between the Fed and Banks. We first examine direct rides between the New York Fed and the major commercial banks. Figure 4(a) presents the estimate of the change in rides from the major commercial banks to the New York Fed during each bihourly window of each of the 12 event days.[26]

Figure 4. Changes in Direct Rides and Coincidental Drop-Offs Around an FOMC Meeting



Notes. A separate Poisson regression is run for each intraday window–event day pair, where event day t is an offset of t calendar days from an FOMC announcement. For greater consistency with a typical workday, an intraday window starting during the span from 12:00 a.m. up to and including 4:00 a.m. is mapped to the previous calendar day. The intensity of rides or coincidences is given by Equation (3). Year-month fixed effects, weekday indicators, and overall Manhattan taxi activity are used as controls. To be deemed coincidental, drop-offs must be mapped to the same block, be separated by no more than 1/4 block, be separated by no more than 10 minutes, and not be mapped to the vicinity of a transit hub or any of the FRBNY or commercial-bank buildings. One-sided p-values for coefficients with t-statistics greater than 1.25 are obtained from pairs bootstrapping of year-month observations with at least 1×10^4 repetitions and employ asymptotic refinement. The sample spans 1,425 weekdays from the beginning of 2009 through the end of 2014. The taxi data are from the NYC Taxi and Limousine Commission.

Table 8. Poisson Regression Analysis of Taxi Trips Around FOMC Meetings

	Trip type						
	Commercial bank to FRBNY		Coincidental drop-off of FRBNY and commercial-bank pickups				
Candidate windows (FOMC × intraday):	Single day × all intraday		All spans × all intraday between 9:00 a.m. and 5:00 p.m.				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Change in trips per meeting							
Growth (%)	118.8	6.5	49.8	67.4	2.4	96.1	108.8
t-statistic	(4.39)	(0.75)	(4.35)	(3.98)	(0.36)	(3.83)	(4.30)
Extra trips	0.43	0.23	1.41	1.10	0.24	0.71	0.85
Individual p-value (%)	<0.1	23.5	<0.1	<0.1	35.7	<0.1	<0.1
Robust significance (%)	1.0		1.0	5.0		5.0	1.0
Panel B. Selected FOMC and intraday windows							
Max overall significance	Yes	No	Yes	No	No	No	No
First event day	+1	+1	−2	−1	−1	−1	−1
Last event day	+1	+1	+7	+7	+7	+7	+7
Start of intraday window	1:00 a.m.	1:00 a.m.	10:00 a.m.	11:00 a.m.	11:00 a.m.	11:00 a.m.	11:00 a.m.
End of intraday window	3:59 a.m.	3:59 a.m.	12:59 p.m.	12:59 p.m.	12:59 p.m.	12:59 p.m.	12:59 p.m.
Panel C. Geographic and temporal restrictions							
Only FRBNY neighbors	No	Yes	No	No	Yes	No	No
Extra restrictions[a]	No	No	No	No	No	Yes	No
Only single passengers	No	No	No	No	No	No	Yes
Pseudo-R^2	0.19	0.23	0.08	0.09	0.15	0.07	0.11
Observations	1,425	1,425	1,425	1,425	1,425	1,425	1,425
Candidate models	572		1,690	1,690		1,685	1,690

Notes. Trip types are (i) rides from major commercial banks to the New York Fed and (ii) coincidental drop-offs of passengers picked up near the New York Fed and passengers picked up near major commercial banks. Trips are modeled as Poisson processes with intensity given by Equation (3), and the count of extra trips over the FOMC window is the associated average partial effect over dates mapped to that window times the typical number of weekdays during that window. Coincidental drop-offs do not include coincidences where either drop-off is mapped to the New York Fed, a major commercial bank, or a transit hub. Event day X refers to a date that is offset by X calendar days from an FOMC announcement, with negative values indicating dates before an announcement. Windows beginning during the span from 12:00 a.m. through 4:00 a.m. are treated as part of the preceding calendar day. For direct rides, the set of candidate FOMC windows is the set of single event days from −8 through +7, and the set of intraday windows are all two- and three-hour spans beginning at the top of an hour. For coincidental drop-offs, the set of candidate FOMC windows is the set of all contiguous spans during the period from event day −8 through event day +7, and the set of intraday windows are all two- and three-hour spans beginning at the top of an hour within the span from 9:00 a.m. until 5:00 p.m. All specifications include a control for overall Manhattan taxi activity, weekday indicators, and year-month fixed effects, and all standard errors employ clustering at the year-month level. Individual p-values are right-tail quantiles, are obtained from pairs bootstrapping at the year-month level with 1×10^5 simulations, and employ asymptotic refinement. Sections A.5 and A.6 of the online appendix provide additional details on the estimation and on the variant of the Romano and Wolf (2005) StepM procedure employed in the assessment of data-mining-robust significance. Robust significance of changes for the sample of FRBNY neighbors was not calculated given their individual insignificance. The pseudo-R^2 is 1 − sum of squared residuals/total sum of squares. Counts of candidate models can vary across specifications of the same ride type because of variation in data sparsity. Regressions span a filtered set of weekdays from 2009 through 2014. The taxi data are from the NYC Taxi and Limousine Commission.

[a]The extra restrictions entail the omission of drop-offs mapped to Midtown, the Financial District, and a set of hospitals.

The most statistically significant increases in rides occur in the hours after the end of the FOMC blackout. Rides increase by 0.32 with an individual p-value of less than 0.1% during the 1:00 a.m.–2:59 a.m. window, and by 0.28 with an individual p-value of less than 0.1% during the 2:00 a.m.–3:59 a.m. window. These are also the fourth- and sixth-largest changes in ride count despite their occurrence during typically low-volume intraday windows. The increase between 3:00 a.m. and 5:00 a.m. is also individually significant at the 1% confidence level but is less statistically and economically significant with a magnitude of 0.12 and a p-value of 0.4%. The small and insignificant change between 4:00 a.m. and 6:00 a.m. suggests that the increase is concentrated between 1:00 a.m. and 4:00 a.m.

The postblackout increase in rides remains significant when we adjust for data mining. Examining all two- and three-hour windows, we find that the most significant increase occurs during the span from 1:00 a.m. through 3:59 a.m. after the lifting of the FOMC blackout, and the associated increase is significant at the 1% confidence level even when we account for the data mining over 572 models (Table 8, column (1)).[27] This increase is highly localized: We do not find a large or significant increase in drop-offs at neighboring blocks but more than 100 feet from the New York Fed's blocks (column (2)). Overall, these results are consistent with Prediction 2 that Fed–bank interactions increase immediately following the lifting of the blackout.

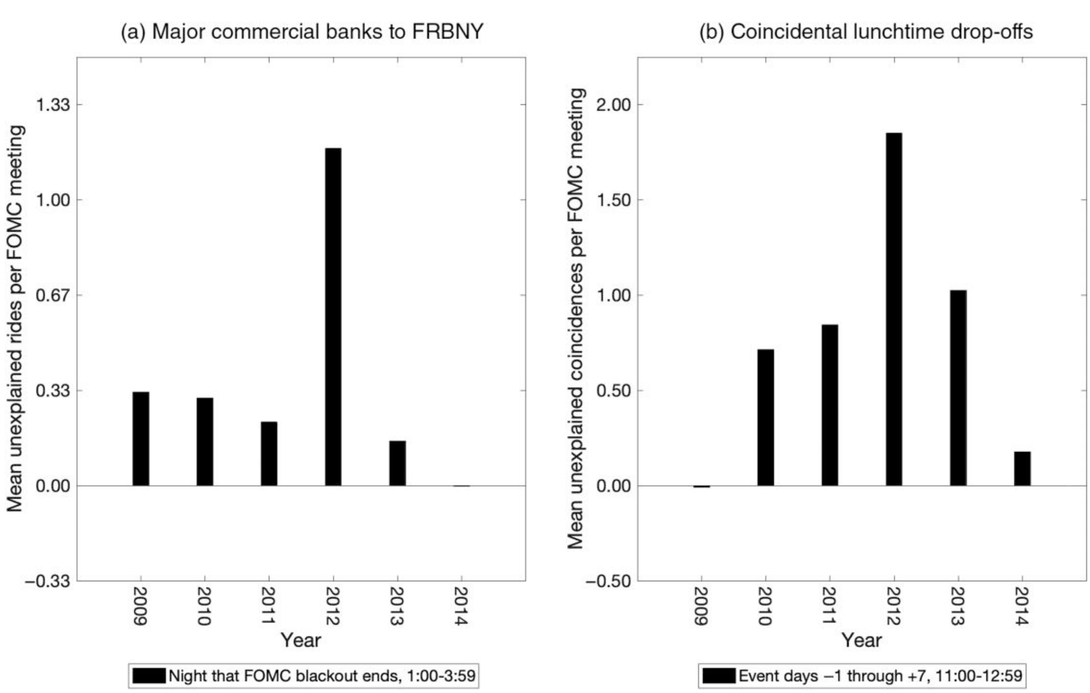
In Figure 4, panel (b) is the analog of panel (a) for rides from the New York Fed to the major commercial banks. Unlike rides in the opposite direction, the lowest individual p-value in a set of hundreds is only 0.5%. Whether this reflects a difference in cabs' availability or an asymmetry in travel is unclear.

To obtain a more complete picture of what underlies the postblackout increase in rides to the New York Fed, we examine the volume of rides unexplained by year-month, weekday, and Manhattan taxi-activity controls. Figure 5 presents each year's mean postblackout ride residual for the 1:00 a.m.–3:59 a.m. window. The mean residual is generally nontrivially positive and never nontrivially negative, but the change in rides estimated over the full sample is clearly driven to a large degree by 2012. In 2012, there were on average roughly 1.18 unexplained rides to the New York Fed in the hours after the end of the FOMC blackout period. This outlier coincides with the year of the Fed's adoption of an explicit inflation target and its initiation of a third round of quantitative easing, QE3. We observe only one ride in the wake of the blackout period around the QE3 announcement, but the second-highest volume over all 1:00 a.m.–3:59 a.m. windows, four rides, occurred after the subsequent blackout period, and the third-highest, three rides, after the previous.

4.2.2. Intraday Changes in Coincidental Drop-Offs. During the blackout period, we expect the number of Fed–bank interactions occurring away from the Fed and bank offices to increase for a couple of reasons. First, some Fed and bank employees might substitute away from formal work interactions that occur often during normal times but are discouraged during the blackout period to social interactions during the blackout period. Moreover, our finding in Section 4.1 that there are significantly elevated Fed–bank interactions around LSAP announcements together with Cieślak et al. (2019) suggest the possibility of information flow from the Fed to the banks during the blackout period. If Fed employees engage in interactions during which such information flow might occur, they might prefer discreet meetings away from Fed and bank offices.[28] We employ coincidental drop-offs away from the New York Fed and the major commercial banks as noisy indicators of informal meetings that occur away from Fed and bank offices. "Coincidental drop-offs" will henceforth imply coincidental drop-offs away from the New York Fed and the major commercial banks' buildings.

For drop-offs to be considered coincidences, they must satisfy three spatial criteria and one temporal criterion. Because coincidences are used to capture meetings away from the financial institutions, the first spatial criterion is that neither ride's drop-off be mapped to the

Figure 5. Assessment of Individual Years' Contributions to the Estimated Increases in Direct Rides and Coincidental Drop-Offs



Notes. Intraday counts are regressed only on year-month fixed effects, weekday controls, and overall Manhattan taxi activity, and the mean of the unexplained counts over each year's FOMC windows is plotted. More precisely, we obtain for each year the mean residual over days in the specified FOMC window and multiply that mean by the typical number of weekdays over that window. A higher mean is suggestive of a greater contribution to the increase over the FOMC window estimated using the full sample. The sample spans 1,425 weekdays from the beginning of 2009 through the end of 2014. The taxi data are from the New York City Taxi and Limousine Commission.

New York Fed or any of the major commercial banks. The second is that the drop-offs be mapped to the same census block. With roads in Manhattan largely following an approximately north–south (NS)/east–west (EW) grid arrangement, the final spatial criterion is that the drop-offs be within a certain distance of each other along the NS axis and along the EW axis. The baseline distance is a quarter of a typical Midtown Manhattan block along its shorter edge, 66 feet (Pollak 2006). This makes some allowance for GPS noise and for dispersion in where individuals are dropped off. The baseline temporal criterion is that the drop-offs be no more than 10 minutes apart. Counts include only coincidences for which both drop-offs are in the specified intraday window, precluding, for example, a drop-off at 11:06 a.m. only coincidental with a drop-off at 10:58 a.m. from contributing to the count for the 11:00 a.m.–12:59 p.m. window.[29] We ignore coincidental drop-offs at Pennsylvania Station and the Grand Central Terminal as well as their adjacent blocks because of an expectation that coincidences around those transit hubs are unlikely to reflect meetings. Coincidences are not common, with the mean count over a bihourly window never exceeding 0.45. The maximum over a bihourly window is five, so there are no extreme outliers (Figure 3(d)).

We again begin by examining variation during overlapping bihourly windows over the 12 event days around an FOMC meeting (Figure 4(c)). The 1:00 a.m.–2:59 a.m. through 5:00 a.m.–6:59 a.m. windows are omitted because of a paucity of observations. Coincidental drop-offs around noon are consistently elevated from the day before the FOMC announcement onward. That starting point typically corresponds to the first day of an FOMC meeting. Moreover, midday changes within a day of the FOMC announcement are individually statistically significant: an increase of 0.19 the prior day between 11:00 a.m. and 1:00 p.m. is individually significant at the 5% confidence level; an increase of 0.20 the day after the announcement between 11:00 a.m. and 1:00 p.m. is individually significant at the 5% confidence level, and an increase of 0.25 the day after the announcement between 12:00 p.m. and 2:00 p.m. is individually significant at the 1% confidence level. A third individually significant lunchtime change is an increase of 0.14 on event day +5 between 12:00 p.m. and 2:00 p.m.

The midday increase in coincidences is significant even when we account for data mining. We follow a similar procedure to that for direct rides, but, motivated by the multiple event days during which we see increases, we also data mine over spans of event days.[30] The most significant windows are 10:00 a.m. through 12:59 p.m. on event days −2 through +7 (+49.8%, 1.41 coincidences; Table 8, column (3)), and the increase is significant at the 1% confidence level. Focusing on hours more likely to reflect lunch, we find that an increase between 11:00 a.m. and 1:00 p.m. on event days −1 through +7 is significant at the 5% confidence level (+67.4%, 1.10 coincidences; column (4)) and that this increase is highly local to the New York Fed (column (5)).

Financial firms are concentrated in Midtown and the Financial District, and the omission of both of these areas where drop-offs might be related to official duties and of hospitals where clusters are also observed yields an increase of 0.71 coincidences (+ 96.1%) and significance at the 5% confidence level when we account for data mining (column (6)). The lunchtime coincidences are largely concentrated in areas associated with dining and shopping like the Meatpacking District and TriBeCa (Figure 6).[31] Restricting rides to those with only a single reported passenger yields a more statistically significant lunchtime increase (column (7)), which suggests that we are not just finding groups of Fed employees going for lunch together at popular locations. Federal Reserve staff who broadly restrict their interactions with outside parties during the blackout might address pent-up demand by scheduling an above-average volume of meetings in the days after its end. Whatever the intent might be, sensitive information could flow even accidentally.

5. Concluding Remarks

We use taxi cab ridership as a novel proxy for Fed–bank face-to-face interactions. We find a negative correlation between past Fed–bank interactions and the stock market's returns around future Fed public announcements, which is consistent with the Fed's choice to acquire more information when it has observed negative private signals about the underlying state of the economy. Cross-sectional tests suggest that this relation between past ridership and future returns around Fed announcements is not driven by the Fed's monetary policy decisions per se, but, rather, the Fed's private information that led to its monetary policy decision.

We also find that there are significantly more Fed–bank interactions immediately following the midnight end of the blackout period, and we present evidence of an increase in the number of off-site lunchtime meetings during the blackout period. We document a significant increase in the number of Fed–bank interactions on the day before the Fed makes announcements regarding quantitative easing, particularly when the Fed is either announcing a new round or an expansion of a round of an ongoing quantitative easing. An important caveat is that our period of study is relatively short (January 2009–December 2014) and unique in that the federal funds rate was effectively zero.

There are likely good reasons for Fed–bank meetings to occur because the Fed can gather additional information and improve its policy actions. The Fed has implemented a blackout period around its FOMC announcements aimed at preventing the flow of monetary policy-related information from the Fed to market

Figure 6. Locations of Lunchtime Coincidental Drop-Offs Around FOMC Announcements

Notes. The lunchtime period spans 11:00 a.m. through 12:59 p.m. The window around an FOMC meeting spans the day before the announcement through a week after the announcement. To be deemed coincidental, drop-offs must be mapped to the same block, be separated by no more than 1/4 block along both the north–south axis and the east–west axis, be separated by no more than 10 minutes, and not be mapped to any of the FRBNY or major-commercial-bank buildings. The outlined areas are based on New York City neighborhood tabulation areas (NTAs). Midtown comprises the Midtown–Midtown South and Turtle Bay–East Midtown NTAs, Chelsea/Flatiron/Union Square/Hudson Yards comprises the Hudson Yards–Chelsea–Flat Iron [*sic*]–Union Square NTA, SoHo/TriBeCa comprises the SoHo–TriBeCa–Civic Center–Little Italy NTA, and the Financial District comprises Battery Park City–Lower Manhattan and parkland. The sample period is 2009 through 2014. The block and NTA boundaries are from the New York City Department of City Planning. The taxi data are from the New York City Taxi and Limousine Commission.

participants. However, our finding that the Fed collects more information when they have negative information that is not yet impounded into market prices suggests it is unlikely that the Fed's blackout period totally prevents information flow from the Fed to banks.

There are many potential avenues for future research. One of the main contributions of our paper is validating that taxi cab ridership provides a new, reliable measure of face-to-face interactions. Other researchers can use our method to examine how face-to-face interactions between employees at financial institutions and their connections relate to capital market phenomena.

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Endnotes

[1] The New York Fed provides an ideal setting to investigate our research question. Many of the largest, most complex, and systemically important financial institutions are headquartered in New York. In addition, the Fed's monetary policy decisions are largely implemented by the New York Fed's trading desk, where all of the Federal Reserve System's open market operations are executed. Finally, the New York Fed is the only regional Fed branch whose president has a permanent spot on the FOMC. For these reasons, the New York Fed is widely considered to be the most important of the 12 regional Fed banks.

[2] An analysis of the cross-section of stock returns reveals that the predictability is strongest among the stocks that benefit least from expansionary monetary policy as measured by Ozdagli and Velikov (2020). This result is difficult to reconcile with an alternative story whereby Fed–bank interactions are simply elevated prior to the Fed's announcements of contractionary monetary policy surprises. Rather, it suggests that Fed–bank face-to-face interactions are typically elevated when the Fed or banks have negative private information about the state of the economy (and when the Fed is thus more likely to engage in *expansionary* rather than contractionary monetary policy) that has not yet been fully incorporated into market valuations.

[3] See also Thorbecke (1997), Bernanke and Kuttner (2005), Chen (2007), Bomfim (2003), Brusa et al. (2020), Cieślak and Vissing-Jørgensen (2021), and Ozdagli and Velikov (2020) for evidence on the relation between Fed policy and stock returns.

[4] There are also several other papers using taxi and Uber data to address nonfinancial topics. See, for example, Cramer and Krueger (2016), Mammen and Shim (2018), Farber (2015), Brodeur and Nield (2017), Jackson (2019), and Cohen et al. (2016).

[5] Green taxis are prohibited from providing hail service to passengers below West 110th Street and East 96th Street. Thus, green cabs cannot service any of the financial institutions in our sample.

[6] Additional limitations to the taxi data are the absence of explicit passenger identifiers and affiliations, the absence of pickup and drop-off addresses, and a lack of information on black cars and other modes of transit.

[7] For our analysis of intraday ridership, we omit dates on which ride counts are unlikely to reflect FRBNY and US G-SIB insiders' behavior or might be unreliable. These dates fall into six categories: weekends, federal holidays, dates around federal holidays with anomalously low ride volumes, hurricanes, hurricane-level disruptions, and highly anomalous reporting by at least one of the Commission's data providers. Details are available upon request.

[8] Goldman Sachs relocated in 2009, and we examine their new headquarter location in all our analysis except for one data validation exercise that centers around the relocation. Although non-American G-SIBs such as Deutsche Bank and HSBC appear to have large New York City footprints, an absence of data on staff sizes and building occupancy complicates a staff-size-based assessment of which buildings to include. Conversely, State Street and Wells Fargo are U.S.-based G-SIBs, but they do not report comparably important presences in New York City. Fed insiders' interactions with non-G-SIB asset managers might also be of interest, but it is less clear where there should or would be relationships, and identification would be significantly hampered by asset managers' generally smaller footprints. Note that, based on June 2019 asset values, the banks used in our sample represent 79% of NYC-headquartered large bank holding companies' total assets, which are more than $10 trillion (source: Federal Financial Institutions Examination Council, National Information Center, www.ffiec.gov/NPW). Including Bank of America increases this to almost 84%.

[9] Figures A.4 and A.5 in the online appendix illustrate specifically how we construct an expanded perimeter around a census block.

[10] We focus on Fed ridership rather than bank ridership because the submission and passage of legislation are presumably more relevant to New York Fed staff than ongoing negotiations, and it is not immediately clear that commercial banks would see the New York Fed as a potentially valuable agent for lobbying Congress.

[11] This might partially reflect consultations with the major law firm Milbank, Tweed, Hadley & McCloy LLP (Milbank), but the finding of high volumes is robust to the exclusion of rides with pickups or drop-offs within 100 feet of Milbank's headquarters (Table 1, panel B; Figure 2(d)).

[12] See https://web.archive.org/web/20220826234528/https://www.chicagofed.org/research/dual-mandate/dual-mandate.

[13] We assume that the Fed's monetary policy is not procyclical. The model that we develop in Section A.1 of the online appendix can accommodate both countercyclical monetary policy, which smooths the business cycle, as well as monetary policy that has no effect on economic output. Moreover, when the Fed is initially pessimistic about the condition of the economy, we do not expect it to stimulate the economy so much that it is ex post (after its expansionary monetary policy decision) more optimistic about the condition of the economy than it would have been had it initially been optimistic about the state of the economy.

[14] In unreported tests, we find that our main results are similar using year-month fixed effects instead of benchmarking it to rides in the previous two weeks. Thus, we are confident that the relations we observe are due to variation in Fed–bank ridership over the previous two weeks, not from ridership levels during our benchmark period.

[15] A complete list of Fed testimony before Congress during our sample period can be found at https://www.federalreserve.gov/newsevents/testimony.htm.

[16] Generally, FOMC announcements are made on Wednesday, so the $\{FOMC_{event\ day+s}\}_{s=-2}^{2}$ indicator variables generally span Monday through Friday of the FOMC week.

[17] See Table A.2 in the online appendix for a description of each LSAP announcement during our sample period.

[18] These are the March 18, 2009; November 3, 2010; September 21, 2011; September 13, 2012; and December 12, 2012 FOMC announcements.

[19] This is calculated as 0.50 + 1.32 + 2.79 = 4.61.

[20] We report the LSAP announcement information for each of the 14 meetings in Table A.2 in the online appendix.

[21] Activity at 1:30 a.m. on a given date, for example, is mapped to the previous date.

[22] In the case of the Wednesday FOMC announcements, which dominate the sample, the weekdays during the span that we examine are the 12 event days −8, −7, −6, −5, −2, −1, 0, +1, +2, +5, +6, and +7. Tuesday FOMC announcements and the single Thursday FOMC announcement also permit the estimation of changes for event days −4, −3, +3, and +4, but we do not examine those event days individually, as the paucity of observations would make their estimates unreliable. Section A.5 of the online appendix discusses the handling of sparse data.

[23] Drop-offs may cluster around typical meeting times, and these windows will capture drop-offs on both sides of the top of an hour.

[24] The MLE fixed-effects Poisson estimator can be consistent for the parameters in λ_t^f even when the ride data do not resemble Poisson draws (Wooldridge 2010). Cameron and Trivedi (2013) provide the estimator specialized to a conditional mean that is exponential in a term that is linear in parameters. They also note that the consistency depends on strong exogeneity, and it is not obvious that the exclusive use of period controls and contemporaneous aggregate taxi activity as regressors would necessarily lead to any important violation.

[25] To minimize the risk of a false rejection of the null, we test against zero change. We obtain one-sided p-values from pairs bootstrapping with asymptotic refinement (see, e.g., Cameron et al. 2008, Cameron and Trivedi 2009). Each bootstrap simulation entails 72 year-month draws with replacement. We employ 1×10^4 simulations when assessing significance up to the 1% confidence level and 1×10^5 simulations when assessing significance up to the 0.1% confidence level. Section A.5 of the online appendix provides additional technical details.

[26] The Poisson regressions yield fractional changes. To obtain a change over an FOMC window in units of rides, we calculate the mean partial effect over those event days, that is, the mean estimated difference in rides of having the indicator on relative to the counterfactual of having it off for the calendar days in the sample mapped to those event days. Later, where an FOMC window may be longer than one event day, we multiply the average partial effect by the typical number of weekdays during that window.

[27] The online appendix discusses in detail the data mining and the calculation of data-mining-robust p-values based on Romano and Wolf (2005).

[28] It is, of course, possible for information pertinent to monetary policy to flow during such interactions both accidentally and for entirely legitimate reasons.

[29] One complication is that a single New York Fed drop-off might be coincidental with more than one drop-off from the major commercial banks or vice versa. Because the interest is in meetings and not individuals, we calculate the number of coincidental drop-offs over an intraday window as the minimum of (i) the number of rides originating at the New York Fed with drop-offs that are coincidental with rides originating at the major commercial banks and (ii) the number of rides originating at the major commercial banks with drop-offs that are coincidental with rides originating at the New York Fed.

[30] Details are provided in the online appendix.

[31] As with post-blackout rides to the New York Fed, 2012 contributes importantly to the estimated increase in lunchtime coincidental drop-offs. Figure 5(b), shows that the mean volume of unexplained coincidences per FOMC meeting is reasonably large and positive from 2010 through 2013 and is only negative, but trivially so, in 2009. Although scarcely exceeding one extra coincidence in any other year, it reaches 1.85 in 2012.

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