What Insights Do Taxi Rides Offer into Federal Reserve Leakage?

David Andrew Finer
Booth School of Business, University of Chicago

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Stigler Center for the Study of the Economy and the State
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5807 S Woodlawn Ave
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Abstract

In this paper, I employ anonymous New York City yellow taxi records to infer variation in interactions between insiders of the Federal Reserve Bank of New York (New York Fed) and insiders of major commercial banks around Federal Open Market Committee (FOMC) meetings. Taxi rides between the vicinities of the New York Fed's and the major commercial banks' buildings serve as indicators of meetings at those institutions, and coincidental drop-offs of passengers picked up around those institutions serve as indicators of offsite meetings. Cieślak, Morse and Vissing-Jørgensen (2016) posit systematic leakage from the Federal Reserve around FOMC meetings along unofficial channels, and, in line with that hypothesis, I find highly statistically significant evidence of increases in meetings at the New York Fed late at night and in offsite meetings during typical lunch hours.

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† The University of Chicago Booth School of Business, 5807 South Woodlawn Avenue, Chicago, Illinois USA 60637, E-mail: dfiner@chicagobooth.edu.

1 Introduction

One of the more dismal aspects of the dismal science is the trade-off between the richness of data and one's freedom to work with them. I exploit a notable exception: the New York City taxi regulator's publication of anonymous yellow taxi pick-up and drop-off records back to 2009. In this paper, I assess whether the variation in opportunities for information flow from the Federal Reserve Bank of New York (FRBNY, New York Fed) to major US commercial banks with large front-office presences in New York City implied by the ride data are consistent with the hypothesis in Cieślak, Morse and Vissing-Jørgensen (2016) that there has been systematic information leakage from the Federal Reserve.[1]

Cieślak, Morse and Vissing-Jørgensen (2016) present evidence that the equity premium has largely been earned in the weeks of Federal Reserve monetary-policy meetings and, drawing on a corpus of anecdotes, hypothesise that unofficial Federal Reserve communication around these meetings is responsible. To shed light on Federal Reserve communication, I use direct rides between the vicinities of the New York Fed and the major commercial banks as indicators of onsite meetings, and I use coincidental drop-offs of passengers picked up around those institutions as indicators of offsite meetings. Interactions need not be face-to-face; other modes of transportation like black cars and the subway are available, and I might not capture all of the relevant taxi rides, so this work provides a lower bound on changes in opportunities for information flow from the FRBNY to the sample of major US commercial banks.

The first data that I examine are direct rides between the vicinities of the New York Fed and the major commercial banks. I consider all two- and three-hour windows beginning at the top of an hour on each weekday from the seventh day before the typical start of a Federal Open Market Committee (FOMC) meeting through the seventh day after the FOMC announcement. While I find few economically and highly statistically significant changes, a striking exception is an increase in late-night rides from the major commercial banks to the New York Fed soon after the end of the FOMC communications blackout. Tight restrictions on Federal Reserve staff communications are lifted at midnight the day after the FOMC announcement, and rides to the FRBNY are elevated

[1]Specifically, I employ the set of US G-SIBs' corporate, investment-banking, investment-management and global-markets headquarters that are listed as properties in 10-K filings and are located in Manhattan.

between 1:00 and 4:00.[2] The change is not large at slightly under half a ride per meeting, but it is an increase of approximately 100% and has an individual p-value far below 0.01. This increase remains highly significant when I assess significance conditional on data mining by following the Romano and Wolf (2005) StepM procedure. Both the significance and the salience of the increase are robust to variations in geographic specifications, covariates, window-selection approach and estimation method. Figure 6 Panel A presents yearly averages of the post-blackout rides that are not explained by year-month fixed effects, weekday controls and overall Manhattan ride volume for 2009 through 2014, and the average is consistently positive. One sees, however, that the estimated per-meeting increase is driven importantly by FOMC meetings in 2012, the year during which QE3 was announced, and an inflation target was formally introduced. Information-seeking or dissemination very soon after the lifting of strict restrictions on the discussion of monetary-policy matters is not implausible.

The taxi data may shed light on interactions away from the New York Fed and major commercial banks. Individuals might meet at a restaurant, café, shop or park, for example, so I also examine variation in the volume of coincidental drop-offs of passengers who depart from the vicinities of the New York Fed and the major commercial banks. I find that coincidences around noon are consistently and strikingly elevated in the days around FOMC meetings. I let the data determine the span over which lunchtime coincidences are significantly elevated. For each two- and three-hour intraday window, I separately perform a Poisson regression of coincidences on indicators for each contiguous span of weekdays from a week before the typical start of a meeting through a week after its end. I balance statistical and economic significance and choose the span with the highest average over its quantile by test t-statistic and its quantile by extra rides. While there is some minor variation across specifications, the period with elevated rides is roughly the day before the FOMC announcement through a week after the announcement, and the intraday window always includes the span from 11:00 until 13:00. Figure 6 Panel B presents average per-meeting unexplained lunchtime coincidences for 2009 through 2014, and while they are consistently elevated, they too are particularly high in 2012.

I find slightly over one extra lunchtime coincidental drop-off around each FOMC meeting, an increase of 50% to over 100% depending on the specification. The increase generally has an

[2] I exclusively employ a twenty-four-hour clock.

individual p-value of below 0.001 and remains significant at a conventional level when the Romano and Wolf (2005) StepM procedure is employed to account for data mining. The significance of the increase passes a large battery of robustness checks and placebo tests, including the definition of a coincidence; pre-specification of windows; and changes in covariates, geographic parameters, estimation method and the approach to window selection. Consistent with informal interaction over lunch, the increase in coincidental drop-offs during the FOMC window largely occurs in areas associated with dining and shopping.

Between direct rides and coincidental drop-offs, I find evidence suggestive of approximately 1.6 extra meetings between individuals associated with the New York Fed and individuals associated with major banks around each FOMC announcement. The timing and locations of the rides imply unofficial or discreet interactions, though this certainly need not imply any impropriety. Given the large increases in percentage terms and the presumably small slice of potential interactions captured by the taxi rides, this estimate is likely highly conservative for the total change in opportunities for information flow. One possible explanation is that New York Fed staff reduce their interactions with commercial bankers during the blackout, and interactions increase thereafter as pent-up demand is addressed. Federal Reserve staff may also seek information from outside parties to facilitate the implementation of monetary policy. Whatever the purpose, interactions between Federal Reserve staff and commercial bankers entail the risk of at least accidental information flow.

The academic literature has employed the New York City taxi data in analyses of the taxi industry and broad patterns of movement within cities, *e.g.* Buchholz (2017), but their utility as metadata in the study of individual businesses and economic sectors has to the best of my knowledge remained unexplored. The closest paper to this work is Koudijs (2016), which examines drivers of eighteenth-century stock-price movements using data on the ships that conveyed news. Taxis can serve as a contemporary means of information transmission in a city and permit higher-resolution insights into the identities of the interacting parties. Yermack (2014) employs movements of corporate jets to study CEO vacations and their business correlates, and I complement that work by using within-Manhattan trips in an examination of the more banal activities of a broader set of workers. Brown and Huang (2017) use public White House visitor logs to study the relationship between executives' access to policymakers and their firms' activities and outcomes, but their data only capture on-site interactions for which the existence of a public record could be assumed. The computer-science literature provides examples of de-anonymisation of individuals' mobility data given collateral information, and this work is a firm-level analogue (*e.g.*, Golle and Partridge 2009 and Hicks and Srivatsa 2012).

While this is new ground for finance and economics, traffic analysis – the study of the structure and workings of networks through communications metadata – has been an important input into intelligence analyses for decades (Nolte 1996, Nolte 1997, Center for Cryptologic History 2006). My insights into this work are limited to public-domain releases, and they offer more in terms of military-historical interest than guidance for work here (*e.g.* Center for Cryptologic History 2006). Danezis and Clayton (2007) provide a qualitative overview of the history of traffic analysis and computer-science applications. In this paper, I make a methodological contribution to the academic literature in the presentation of a roadmap from raw taxi data to inference on meetings.

The paper is structured as follows. In Section 2, I provide background on FOMC meetings and the New York Fed, describe the data and validate that the taxi rides are informative about the business activities of the major commercial banks and the New York Fed. In Section 3, I investigate variation around FOMC meetings both in direct rides between the vicinities of the New York Fed and major commercial banks and in coincidental drop-offs of passengers picked up around them. Section 4 discusses the results, and Section 5 concludes.

2 Background and data

2.1 Federal Open Market Committee (FOMC) meetings

The highest-profile Federal Reserve (Fed) meetings are Federal Open Market Committee (FOMC) meetings. Senior Federal Reserve officials meet eight times per year in Washington D.C. to discuss economic developments and forecasts and to decide upon the federal funds target range and unconventional monetary policy. These meetings are immediately followed by a public announcement of policy decisions, but minutes are not released until weeks later and transcripts not until years later. Access to particularly sensitive inputs into and products of FOMC meetings such as the Tealbook and transcripts is generally restricted to a small set of specified staff on a need-to-know basis (Board of Governors 2014). The New York Fed and the Board of Governors are special cases, and while dissemination is still formally limited to those with a need to know, there is not a fixed limit to the number of eligible recipients (Board of Governors 2014).

Communication with the public around FOMC meetings is subject to tight restrictions. During a blackout period, Federal Reserve staff are not permitted to discuss with the public monetary-policy and economic matters that have not already been cleared and widely disseminated. Over the period examined in this paper, the blackout began a week before the FOMC meeting's first day and ended a day after the announcement (Board of Governors 2014).[3] A sample timeline of Federal Reserve events around FOMC meetings is presented in Table A.2.

Despite the rules, FOMC information has reached the public before its official release. In the late 1980s and early 1990s, for instance, FOMC decisions were only to be released after a substantial lag, but the Wall Street Journal frequently wrote about them within a week of the meetings (Cieślak, Morse and Vissing-Jørgensen 2016). More recently, private media firm Medley Global Advisors circulated information on FOMC deliberations prior to their authorised release (Appelbaum 2017). Cieślak, Morse and Vissing-Jørgensen (2016) use anecdotes and patterns of excess returns on S&P 500 futures around FOMC meetings to argue that market-moving information systematically flows from Federal Reserve insiders to outside parties through informal communication. Bernile, Hu and Tang (2016) present market data that they interpret as informed trading in the minutes prior to FOMC surprises. The possibility of systematic leakage is controversial, and Lucca and Moench (2015) present counter-arguments. In recent years members of the Board of Governors have met in Washington D.C. immediately prior to FOMC meetings to discuss the regional Federal Reserve Banks' proposals for the primary rate, and Cieślak, Morse and Vissing-Jørgensen (2016) argue that systematic leakage from these meetings or of support material for them might also occur. Cieślak, Morse and Vissing-Jørgensen (2016) report that unlike for FOMC meetings, transcripts are not available for these discount-rate meetings and suggest that this may be conducive to particularly frank discussions among the policymakers.

2.2 The Federal Reserve Bank of New York

The Federal Reserve Bank of New York (FRBNY, New York Fed) plays a special rôle in the Federal Reserve System. On the monetary-policy side, it hosts the staff responsible for performing

[3] Revisions to the policy in January 2017 expanded the blackout period and further restricted permissible communication (Board of Governors 2017).

the Fed's open-market transactions including those intended to move the federal funds rate towards the target set by the Federal Open Market Committee, those authorised under Large-Scale Asset Purchase (LSAP) programmes and those involving foreign currency (Board of Governors 2005, Federal Reserve Bank of New York 2010b). Unlike the other regional Federal Reserve Banks, there is not a fixed limit to the number of eligible recipients of sensitive FOMC information, though access is still required to be on a need-to-know basis. The New York Fed also operates the discount window from which New York City banks, broadly speaking, can obtain short-term funding (Federal Reserve Bank of New York 2015). On the regulatory side, the New York Fed supervises financial institutions legally located in New York City's Federal Reserve District (Federal Reserve Bank of New York, n.d.(d)). Like the other regional Federal Reserve banks, it provides economic briefings to the Federal Reserve System and provides data in support of FOMC deliberations (Board of Governors 2005). For example, the New York Fed formally surveys primary dealers and other market participants to obtain their expectations for financial markets, the broader macroeconomy and Federal Reserve actions (Federal Reserve Bank of New York, n.d.(c), Federal Reserve Bank of New York, n.d.(e)).

The importance that the New York Fed places on interaction with the financial sector is manifest in its expectations of primary dealers – the institutions that may transact in securities with the FRBNY – and in its numerous advisory groups. The New York Fed explicitly states that it expects primary dealers to "provide the New York Fed's trading desk with market commentary and market information and analysis helpful in the formulation and implementation of monetary policy" and indicates that maintenance of primary-dealer status is contingent on the quality of that commentary (Federal Reserve Bank of New York 2010a). Bankers and asset managers are members of the Economic Advisory Panel, the Financial Advisory Roundtable and the Investor Advisory Committee on Financial Markets, for instance, and in the overview of the groups, the New York Fed notes that "[t]hese interactions help the New York Fed to provide timely information to the Federal Reserve System and to support the formulation and implementation of monetary policy effectively" (Federal Reserve Bank of New York, n.d.(b)).

2.3 Flow of information from the Federal Reserve System

Anytime that Fed insiders interact with commercial banks' insiders or at least are in close proximity is an opportunity for both intentional and accidental disclosure of data. Even the broad topics raised by Federal Reserve insiders can reveal information. Laurence Fink, the CEO of BlackRock, indeed explicitly stated to the Wall Street Journal that insights into the Federal Reserve can be obtained from questions that it posed to members of the private sector (Pulliam 2011). Then-Governor Yellen noted during the 2-3 November 2010 FOMC meeting that external parties can induce problematic disclosures (Federal Open Market Committee 2010).[4] Indeed, the Richmond Fed president resigned in April 2017 over inappropriate communication with a journalist at Medley Global Advisors. He claimed that when the reporter raised non-public details of FOMC monetary-policy deliberations, his omission to declare his inability to discuss the matter might have signalled its veracity (Appelbaum 2017).

Despite such risks, some Fed employees might find it challenging to impose strict limitations on the volumes of their interactions with external parties lest they should harm relations that are important both for the conduct of Fed business and for those employees' external employment options (Zingales 2013 and Lucca, Seru and Trebbi 2014 for the intuition). When sensitive topics might be raised, both parties might prefer face-to-face meetings. Anecdotally, journalists' contacts can prefer to meet for coffee when sensitive topics come up. Analogous meetings could perhaps be inferred from taxi rides. A party seeking insights into the Federal Reserve might also prefer a face-to-face meeting with her Federal Reserve asset due to the ability to glean additional information from non-verbal signals and, when meetings occur at the New York Fed, from the level of activity there.

It is not inconceivable that some Federal Reserve information not already in the public domain may be intentionally disclosed for monetary-policy purposes. Bernanke (2004) explains how transparent decision-making and clear strategies on the part of the FOMC can enhance financial stability. He also discusses the challenges of setting monetary policy when the state of the eco-

[4]"We're obliged to maintain the confidentiality of FOMC information – period, full stop. And that includes documents that we look at in the FOMC and information on who said what. It's obvious that these guidelines have been breached. I also know from personal experience over the years that it's easy for this to happen – it can happen pretty innocently when an experienced reporter lures one into revealing things that end up crossing the line." (Federal Open Market Committee 2010)

nomy and the impacts of mooted central-bank actions are unknown. It follows that substantive discussions with market participants could be beneficial on all of those fronts. Blinder et al. (2008) argue that individual policymakers' speeches and interactions with journalists can provide signals in between policy announcements. Cieślak, Morse and Vissing-Jørgensen (2016) suggest that continuous informal information flow could be used to provide explanations to market participants and that it could provide the Fed with more flexibility in the implementation of monetary policy in that it would reduce the magnitude of policy surprises and would not entail commitment. They question, however, the value of doing so privately.

2.4 New York City yellow taxi data

The New York City Taxi & Limousine Commission (TLC, the Commission) has released over a billion yellow taxi trip records back to 2009. The dataset is not simply a curiosity for public consumption: the Commission regulates the city's taxi industry and collects the data for official purposes (NYC Taxi & Limousine Commission 2017). While the TLC does not guarantee the completeness and accuracy of the ride data, it audits them and has the authority to take steps to ensure adequate reporting (NYC Taxi & Limousine Commission 2017). These records provide an incredibly rich picture of New Yorkers at work and at leisure, but this is the first academic paper to employ them as metadata in the study of a sector of the economy other than the taxi industry.[5] With firms such as Uber and Lyft collecting the movements of tens of millions of individuals, it is particularly timely to assess the insights into institutions that even data without explicit rider identifiers can provide (Kokalitcheva 2016). One purpose of this paper is to introduce these rich data as a tool that may be employed in a broad set of microeconomic, macroeconomic and financial studies.

TLC ride-level data were first broadly disseminated in 2014 in response to a request under New York State's Freedom of Information Law (Whong 2014). It is conceivable that for most of the period up to 2014, riders would not have expected that their trip details would ever be published. Included in the dataset are each trip's pick-up and drop-off times, pick-up and drop-off GPS coordinates, distance, passenger count, fare, tip and manner of payment, *inter alia*. Inspection

[5] In a blog entry about the New York Taxi & Limousine Commission dataset, Schneider (2015) plots total drop-off volumes against drop-off times for a couple of bank headquarters and infers the broad areas where employees live.

of the dispersion of pick-up and drop-off coordinates around roads suggests that the coordinates are accurate to between $O(10ft)$ and $O(100ft)$, with a greater concentration of highrises introducing greater uncertainty.[6] Coordinates are mostly clustered within 100 feet of a block's border.

As the taxi dataset lacks precise pick-up and drop-off locations, I work at approximately block level. The precise areas to which I map rides are derived from census blocks, which broadly coincide with city blocks. When an institution's building occupies its full block, rides to and from that block are mapped to that institution. When an institution's building occupies only part of its block, only rides to or from that building's slice of the block are mapped to that institution. Motivated by the scatter that I observe around roads, I map rides to expanded versions of blocks or slices thereof obtained by pushing each vertex outward by 100 feet. Subsection B.1 details how the data are cleaned to reduce the influence of records afflicted by GPS and human error, and Subsection B.2 provides additional information about the census-block polygons.

Deficiencies in the taxi data are the absence of passenger identifiers and affiliations and the absence of pick-up and drop-off addresses. The key identifying assumption in this paper is that the events of interest mainly drive variation in interactions between insiders of the institutions of interest. I may not be able to make inferences about levels of interaction, but if this assumption holds, I can identify how rides involving insiders of the institutions of interest respond to those events. While not a problem with the yellow cab records themselves, my lack of access to similar data for black cars and rideshare firms likely precludes the examination of a large set of direct rides and coincidental drop-offs.

2.5 FRBNY and commercial-bank offices

The New York Fed's headquarters at 33 Liberty Street occupies its entire block, and it has staff at 33 Maiden Lane just across the street to the East (Federal Reserve Bank of New York, n.d.(a)). While some financial and legal institutions have operations in the vicinity of the Fed, and a hotel and private residences are located nearby, rides to and from them would have to vary systematically around meetings in Washington, D.C. for them to do more than just add noise. More details on the New York Fed's Manhattan presence and its neighbours are provided in Appendix A.2.

[6] As an example, Figure B.1 presents all of the recorded pick-up and drop-off locations from 2009-2014 in the vicinity of the Federal Reserve Bank of New York's main offices with block outlines superimposed. Figure B.2 presents the distribution of pick-ups and drop-offs around JPMorgan Chase's headquarters in skyscraper-laden Midtown.

To facilitate the identification of rides with interactions between the New York Fed and commercial financial institutions, I employ only large institutions with which New York Fed staff would be expected to have at least a professional relationship. For this set I employ the US-based subset of the Financial Stability Board's Global Systemically Important Banks (G-SIBs) (Financial Stability Board 2014). To maximise the share of rides during which information might flow to active participants in financial markets, I consider only important front-office presences, defined here as locations that are both listed as properties in 10-K filings and serve as corporate, investment-banking, financial-markets or asset-management headquarters. In total, I employ nine locations where Bank of America, BNY Mellon, Citigroup, Goldman Sachs, JP Morgan and Morgan Stanley have offices. All of the banks except for BNY Mellon are also primary dealers, and maintenance of that status entails the provision of market commentary to the New York Fed (Federal Reserve Bank of New York 2010a). One examination includes the headquarters of Goldman Sachs before its 2009-2010 move, but that location is otherwise ignored due to the occurence of the move so early in the sample. The buildings are listed in Table A.1, and their unexpanded areas are plotted on a map of Manhattan in Figure A.1.

While 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 would make a staff-size-based assessment of which to include highly arbitrary. Conversely, State Street and Wells Fargo are US-based G-SIBs, but they do not report comparably important presences in New York City. Fed insiders' interactions with non-G-SIB asset managers may 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.

2.6 Data validation – Relocation of Goldman Sachs's headquarters

Goldman Sachs relocated its headquarters from 85 Broad Street to 200 West Street, and I seek an indication of whether taxi rides reflect the movement of business activity from the old headquarters to the new headquarters. Figure 1 presents two-deviation confidence bands for monthly mean daily rides between each of the old and the new headquarters and the buildings of the other major commercial banks.[7] The decline in the old headquarters' volume and the increase in the new headquarters' volume are strikingly coincident and begin around November 2009, when 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 the highly significant structural breaks in the geography of business interactions that would follow a relocation of a major bank's headquarters. The magnitudes of the changes in volume are different, but usage of taxis, the proximities of pick-ups and drop-offs to the headquarters' block and the relocation of Goldman Sachs employees from other locations could be responsible.

2.7 Data validation – Trips around Dodd-Frank milestones

The Dodd-Frank Wall Street Reform and Consumer Protection Act (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 officials, the institutions that the New York Fed regulates and the Fed staff embedded in those institutions (Paletta and Lucchetti 2010). I examine ride volumes on, before and after the dates listed in the United States Congress's overview of actions on Dodd-Frank with the exception of the long list of dates on which conference committees were held. These events include the introduction of Dodd-Frank to the House; congressional votes and agreements; the filing of a conference report; and the President's signing of the bill into law (U.S. Congress, n.d.). The submission and passage of legislation is 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.

Ride volumes do indeed increase around the Dodd-Frank milestones (Table 1 Panel A). One observes a striking pattern: from the filing of the conference report onward, the day before each milestone is in the top 99.7% of days by ride volume. The day before the Senate agreed to the conference report and the day before President Obama signed the bill into law saw the highest two volumes of the whole sample. High ride volumes are not limited to those days: Figure 2 Panel A presents two-deviation confidence bands around monthly average weekday rides, and overall ride

[7] For greater consistency with boundaries of working days, throughout this paper a day is defined as 5:00 through 4:59 rather than 0:00 through 23:59.

volumes in June and July 2010 are clearly exceptionally high.

One threat to the identification of this variation with Fed activity is that a tower across from the New York Fed houses the headquarters of the major law firm Milbank, Tweed, Hadley & McCloy LLP (Milbank). At least some of the rides could reflect banks' consultations with Milbank's lawyers on matters related to Dodd-Frank. The above results are, however, largely robust to the removal of all rides beginning or ending within 100 feet of Milbank's block (Table 1 Panel B and Figure 2 Panel B). The quantiles for the days before the June and July events do not fall below 98.5%, and June and July 2010 still have exceptionally high overall ride volumes. These together with the unrestricted results suggest that the ride data are indeed informative about FRBNY activities.

3 Empirical analysis

3.1 Sample period

The taxi dataset begins on 1 January 2009, and data with GPS coordinates are available through 30 June 2016. Later data are available but at a very low spatial resolution. I select an earlier endpoint due to concerns over the impact of Uber on the use of taxis for Fed interactions. According to a producer of travel-expense software, Certify, such services' share of expensed rides had increased from roughly one-tenth in early 2014 to roughly one-third in early 2015 (White 2015). In light of growth in the usage of Uber for Business, including by major banks, since its mid-2014 debut, I only examine data from their beginning in 2009 through the end of 2014 (Rao 2015, Saitto 2014). I remove holiday periods, dates during which taxi traffic appears to have been seriously impacted by extreme weather events and dates for which there is strong evidence that substantial volumes of rides are missing for at least one of the providers of taxi data to the Commission. The filtration is discussed in more detail in the Subsection B.4. To maximise the probability that taxi rides are linked to Fed and commercial-bank insiders, I omit weekends except for the early hours of Saturday morning. The filtered sample spans 1425 weekdays or 91.1% of all weekdays from the beginning of 2009 through the end of 2014.

3.2 Summary statistics

Figure 3 Panel A presents summary statistics for aggregate Manhattan taxi activity, the average of pick-up and drop-off volumes of rides within Manhattan. Activity plateaus after 8:00, suggesting that a typical workday has begun by then. Activity is fairly level from 8:00 until 16:00, declines and then rises again from 17:00 until 20:00. That increase in traffic is presumably linked to departures from work and post-work activities. Except for late at night and very early in the morning, volumes are generally negatively skewed. Since aggregate Manhattan activity reaches a nadir between 4:00 and 5:00, and rides very early in the morning are presumably more likely to be long days at work than early starts, my activity-based definition of a day is the span from 5:00 through 4:59.[8] Activity at 1:30 on a given date, for example, is mapped to the previous date.

Rides from the vicinity of the New York Fed to the vicinities of major commercial banks rise from 5:00 to 8:00, with each of the examined quantiles attaining its maximum during the 7:00-7:59 window and the mean peaking at 1.27 (Figure 3 Panel B).[9] Unlike Manhattan as a whole, rides generally decline over the rest of the day. Anecdotally, meetings at financial institutions with external parties are not likely before 8:00, so the coincidence of high morning volumes with the apparent morning commute for Manhattan as a whole suggests that early morning rides from the vicinity of the New York Fed may be largely driven by the commutes of residents of the condominium near the Fed or the hotel across from it. The median ride count is only above 0 from 6:00 until 10:00 and never exceeds 1. There is a clear positive skew in all windows, but while the right tail is long, there are no extreme outliers: the maximum over all windows and days is only 6. The evolution of the means and quantiles of rides from the vicinities of the major commercial banks to the vicinity of the FRBNY resemble those for Manhattan as a whole, though the skew resembles that of rides in the opposite direction (Figure 3 Panel C). The median ride volume is never positive, but the elevated means and quantiles between 21:00 and 0:00 might reflect neighbours of the New York Fed's late departures from work at the commercial banks. The highest mean, 0.64 rides, occurs between 22:00 and 23:00, and the maximum count over all windows is only 6.

[8] In the interest of economy, times of the form XX:00:00 and XX:59:59 are rendered as XX:00 and XX:59.

[9] For the window associated with a ride between the New York Fed and a commercial bank, I arbitrarily choose the window of the drop-off time.

3.3 Ride variation by intraday window

The key identifying assumption in this paper is that FOMC meetings in Washington, D.C. have a much more significant impact on interactions between the New York Fed's and commercial banks' insiders than on interactions involving their neighbours. Even though I cannot infer levels of interaction between New York Fed insiders and commercial-bank insiders around FOMC meetings, I can identify changes if this assumption holds. I consequently focus exclusively on changes in rides around FOMC meetings.

The intraday timing of rides can be at least weakly informative about the interactions that they mediate. For example, mid-afternoon rides would presumably be more likely to reflect appointments than informal activities, and the reverse could be said for Friday nights. In order to exploit the information in when rides occur, I examine variation in rides during a set of intraday windows. The use of intraday windows also eliminates the problem inherent in full-day aggregation that meaningful variation could be obscured by unrelated noise over the rest of a day.

I approach the data with diffuse priors about how a day in the vicinity of the FRBNY is structured. I consequently do not focus on *ad hoc* commute windows and workday windows, for instance, but break the full day into overlapping two-hour windows with each beginning at the top of an hour. While one-hour windows might seem more natural, rides might be clustered on both sides of an hourly division. For example, if two people regularly schedule a drink at 18:00 after FOMC meetings, there might be a cluster of rides from 17:50-18:10. The use of a 17:00-18:59 window could yield double the signal in each of the 17:00-17:59 and 18:00-18:59 windows with less than a doubling of the noise while still suggesting an after-work interaction. The use of bihourly windows also reduces the importance of the choice of whether to map rides to windows by their pick-up or drop-off times. There is no clear disjoint division of a day into two-hour windows, so I employ overlapping windows.

Given that ride counts are discrete and non-negative, I employ Poisson regressions in their analysis. The prototypical regression for rides during intraday window f employs a conditional mean, or intensity, λ_t^f of the following form:

$$\lambda_t^f = exp\Big(\iota_t \beta_\iota + z_t^f \gamma + \alpha_{ym(t)} + \theta_{wd(t)}\Big) \tag{1}$$

where t indexes the date; ι_t is an indicator of whether date t falls in a specified FOMC window, a set of offsets from the nearest FOMC announcement; z_t^f is aggregate Manhattan taxi activity during window f on date t (the mean of all pick-ups and drop-offs of intra-Manhattan rides); $ym(t)$ is the year-month associated with date t; α_{ym} is a fixed effect for year-month ym; $wd(t)$ is the weekday associated with date t, and θ_{wd} is a weekday indicator. The QMLE fixed-effects Poisson estimator used in this paper can be consistent for the parameters in λ_t^f even when the ride data do not resemble Poisson draws (Wooldridge 2010).[10] Cameron and Trivedi (2009) 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. I cluster at the year-month level to accomodate arbitrary heteroskedasticity and within-month serial correlation. The cluster-robust covariance matrix is derived from M-estimation. My null hypothesis for each FOMC window is a non-positive change, and my alternative is a positive change. To minimise the risk of a false rejection of the null, I test against zero change. I obtain one-sided p-values from pairs bootstrapping with asymptotic refinement (see, for example, Cameron, Gelbach and Miller 2008 and Cameron and Trivedi 2009). Each bootstrap simulation entails 72 year-month draws with replacement. I employ 10000 replications when assessing significance up to the 1% confidence level and 100000 replications when assessing significance up to the 0.1% confidence level. Appendix A.3 provides additional technical details.

In the ideal experiment, meeting dates would be scheduled randomly, but they are not. FOMC announcements tend to fall on Wednesdays and, less frequently, Tuesdays. During the sample, no FOMC meetings fell in February, and a disproportionately small number fell in May and July. Monthly and intraweek seasonality in the rides could therefore introduce bias. Disproportionate weighting can also add bias in the presence of low-frequency trends, and I employ year-month indicators to address both trends and monthly cyclicality. I use indicators for Tuesday through Friday to soak intraweek cyclicality up.

A concern with the use of period indicators ι_t to identify causal impacts is that more varies between the on and off dates than the events of interest. Some FOMC windows might just coincide with overall higher levels of taxi activity and have nothing to do with the meetings themselves.

[10] Cameron and Trivedi (2009) provide the estimator specialised to a conditional mean that is exponential in a term that is linear in parameters

While the weeks of the year on which meetings occur do exhibit some variation, the addition of a taxi-activity control is prudent. I therefore include as a covariate the mean of contemporaneous pick-ups and drop-offs of within-Manhattan rides during the same intraday window. Camerer et al. (1997) provide evidence that New York taxi drivers make labour-supply decisions at daily frequency, so the control for overall ride volume may also soak some supply-side variation up and thereby tighten inference.

3.4 Overview of changes in direct rides

A natural starting point to look for variation in rides around FOMC meetings is the first day of the FOMC communications blackout. During the sample period, this begins seven days before the first day of the FOMC meeting.[11] Guided by the timing of market movements in Cieślak, Morse and Vissing-Jørgensen (2016) and symmetry, I choose as an endpoint the seventh day after the FOMC announcement. I map calendar days to event days by obtaining the difference in days from the nearest FOMC meeting, with a negative integer indicating a day prior to the meeting and a positive integer indicating a day subsequent to the meeting.[12] In the case of the Wednesday FOMC announcements which dominate the sample, the weekdays during the span that I examine are the twelve 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 effects for event days -4, -3, +3 and +4, but I do not include indicators for those days as the paucity of observations would make their estimates highly unreliable (Table A.3). So that the estimate for each event-day change does not depend on the particular set of other event days examined, I separately estimate Eq. 1 for each selection of intraday window and event-day indicator.[13]

I first examine the variation in rides from the two New York Fed buildings to the major commercial banks. Figure 4 presents graphically the estimate for the change in rides during each bihourly window of each of the twelve event days.[14] I find some variation that is significant at the 1%

[11] The blackout begins at midnight, but for convenience I begin at the start of the business day as defined in this paper, 5:00.

[12] I define a day as the span 5:00-4:59, and windows beginning at 0:00 through 4:00 on one calendar day are mapped to the previous calendar day and the associated event day

[13] Appendix A.3 discusses the handling of sparse data.

[14] The Poisson regressions yield percentage changes. To map a change associated with an FOMC window to a value in rides, I calculate the average partial effect over those event days, *i.e.* the average 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.

confidence level, but the p-values are not particularly low. There is a large increase between 7:00 and 9:00 on event day +5, typically the Monday after the FOMC announcement. The volume of trips increases by 0.66 rides, and the p-value of 0.005 is among the two lowest of all of the windows. This increase is, however, substantially offset by large decreases between 9:00 and 12:00. The variation the morning of event day +5 may therefore simply reflect a change in the timing of rides. One observes increases of about 0.3 rides with p-values of 0.009 between 10:00 and 13:00 the day after the blackout ends. Also significant at the 1% confidence level is an increase of 0.24 rides between 15:00 and 17:00 on event day −8 with a p-value of 0.004. Some non-overlapping variation is individually significant at the 5% confidence level, but it is scattered and not particularly salient.

An identical analysis of rides from the financial institutions to the two New York Fed buildings shows substantially more significant variation, particularly at night (Figure 5). The largest increase occurs the first night of the blackout: 0.61 from 23:00 through 0:59. Its p-value is 0.001, and rides are significantly elevated at the 1% and 5% confidence level during the two subsequent intraday windows. An increase of 0.35 rides two days later between 21:00 and 23:00 is significant at the 1% confidence level, and the preceding and following windows are significant at the 5% confidence level. A few scattered changes at night and in the morning are significantly positive at the 5% confidence level.

Strikingly, the most statistically significant increases in rides occur back-to-back in the hours after the end of the FOMC blackout, a time when FRBNY staff are again permitted to discuss with outside parties economic and monetary-policy matters that have not already been widely disseminated. Rides increase by 0.38 with a p-value of less than 0.001 during the 1:00-2:59 window and by 0.35 with a p-value of less than 0.001 during the 2:00-3:59 window. These are also the second and fifth largest changes in ride count despite occurring during typically low-volume intraday windows.

3.5 Significance of the post-blackout increase in rides to the New York Fed

I add rigour to the examination of ride variation by undertaking a more formal data-mining exercise in which the assessment of significance accounts for the data mining. I follow the Romano and Wolf (2005) one-sided StepM approach which seeks to maximise the number of rejected null hypotheses for a given type-I error rate. I test for significance at the 10%, 5%, 1% and 0.1% confidence levels.

Romano and Wolf (2005) present a bootstrap-based implementation for use with a very broad class of random variables, but coverage of the tail behaviour of a very large number of specifications necessitates a prohibitively large number of draws. I exploit the asymptotic multivariate normality of the set of coefficient estimates obtained from GMM and instead simulate t-statistics by taking 1000000 draws from an estimate of the coefficients' correlation matrix. I provide details in Appendix A.4.

In light of the volume of robustness checks that I perform, I seek a most-significant pair of intraday and FOMC windows on which to focus. Significant increases may also occur during other windows, so focusing on a single pair yields a lower bound on ride growth. The StepM procedure imposes no constraints on this choice, and I choose to balance statistical and economic significance by choosing the windows that maximise the average of *i.*) the associated model's quantile by the t-statistic of the coefficient on the event indicator; and *ii.*) the associated model's quantile by the estimated increase in rides. Where there is a tie, I choose the model the two quantiles for which have the lowest variance about their mean. There will in general be models with higher t-statistics and models with higher average partial effects.

I expand the set of windows presented in the overview. Since the appearance of back-to-back increases that are individually significant at the 1% confidence level suggests the possibility that particularly important changes are spread over three hours, I augment the set of two-hour windows with all three-hour windows starting at the top of an hour. For each intraday window, I again perform a separate regression for each of the twelve event-day indicators.

Both the salience of the post-blackout increase and its significance are robust to a variety of modelling choices. Almost every specification that I examine selects the 1:00-3:59 window immediately after the FOMC blackout ends as the period with the most significant increase in rides; the individual p-values are very low, and the robust p-values generally indicate significance at conventional levels. In the specification with rides to the vicinities of both FRBNY buildings and with controls for the year-month, weekday and overall Manhattan taxi activity, the estimated change is 0.50 rides (+108.6%) with an individual p-value of less than 0.001 and a data-mining-robust p-value of less than 0.001 (Table 2 Column i, henceforth the baseline specification). The maximum ride count during this intraday window is 4, so these results are not dependent on a large outlier. Little changes when drop-offs are restricted to the vicinity of the FRBNY headquarters at

33 Liberty Street, a constraint which also limits the possible distances between drop-offs and the main entrance to 33 Maiden Lane. The estimate of extra rides drops slightly to 0.43; the percentage increase rises to 120.8%, and the individual and robust p-values are respectively < 0.001 and less than 0.01 (Column *ii*, henceforth the conservative specification). I conclude that the change in post-blackout rides is not significantly driven by the shops, residences and restaurants to the Northeast and East of 33 Maiden Lane, and I focus mainly on the vicinity of 33 Liberty Street in the subsequent robustness checks.

I find that the presence of the control for aggregate Manhattan activity is unimportant, but the year-month and weekday controls have first-order impacts. Removal of the Manhattan control changes the estimate and significance minutely (Column *iii*). When the Poisson regression uses only a constant and the FOMC-window indicator as regressors and employs White standard errors, the chosen window is the evening before the FOMC announcement between 20:00 and 23:00 (Column *iv*). In this case, the increase is 0.68 rides (+50.8%), with an individual p-value of < 0.001 and a data-mining robust one of less than 0.05. Since the FOMC event days generally occur on the same weekday, the coefficients on their indicators will absorb unrelated intraweek cyclicality. The substantial deviation from the baseline and conservative results likely reflects such omitted-variable bias. The significance of the increase from 1:00-3:59 the day after the FOMC announcement, however, does not depend crucially on the inclusion of the temporal dummies and taxi-activity control. The estimate decreases slightly to 0.39 rides (+98.0%), and the individual and data-mining-robust p-values are less than 0.001 and less than 0.1 (Column *v*). It is clear from the pseudo-R^2 that the temporal dummies soak up much of the variation, so the reduction in statistical significance with their omission is not surprising.

The change in rides after the blackout ends is largely robust to changes in the vertex shifts and the method of window selection. For the baseline specification, reduction of the vertex extension to 50 feet yields the same selection of window. The estimated increase in units of rides of 0.34 is about a third lower, but the change is larger in percentage terms, 149.9%, and remains statistically significant (Column *vi*). The selection of window changes when the vertex expansion is increased to 150 feet (Column *viii*), but the estimate of additional rides during the 1:00-3:59 window after the FOMC blackout ends is similar at 0.41 (Column *ix*). The individual p-value is, however, much higher at 0.009, and the change is insignificant when one accounts for data mining. Given that the change with the further outward shift is similar to the other specifications in units of rides but is much small as a percentage, +47.3%, the loss of significance is likely due to the inclusion of a significant volume of noise when more distant pick-ups and drop-offs are added. For the conservative specification, the same windows are selected when one halves the extension to 50 feet or expands it to 150 (Columns *vii* and *x*). In the former case, the estimated change in rides drops to 0.32 (+189.5%), and in the latter it remains 0.43 (+64.6%). Both estimates are individually significant at better than the 1% confidence level (p-values of less than 0.001 and 0.003), but only the reduction is significant when one accounts for data mining (robust p-values of less than 0.01 and greater than 0.1). For both the baseline and the conservative specifications, model selection based only on the t-statistic yields the same windows as one obtains from putting equal weight on the quantile by t-statistic and the quantile by additional rides (Columns *xi* and *xii*). Appendix A.1 demonstrates the robustness of the increase in post-blackout rides to changes in the sample period, changes in how rides are mapped to institutions and the use of OLS with simple standard errors and asymptotic p-values.

To obtain a more complete picture of what underlies these results, I examine the volume of rides unexplained by the year-month, weekday and Manhattan taxi-activity controls. Figure 6 Panel A presents for each of 2009 through 2014 that year's average post-blackout ride residual for the 1:00-3:59 window.[15] As a robustness check, I examine residuals from both the baseline and the conservative specifications. The average residual is consistently non-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 1.2 unexplained rides to the New York Fed in the hours after the end of the FOMC blackout period. 2012 saw the Fed's adoption of an explicit inflation target and its initiation of a third round of quantitative easing. I observed only one ride in the wake of the blackout period around the QE3 announcement, but the second-highest volume over all 1:00-3:59 windows, 4 rides, occurred after the subsequent blackout period, and the third-highest, 3 rides, after the previous. Discreet information-seeking or clarification of Fed communication are not inconceivable. One might hypothesise that information-seeking would increase in 2013 around the so-called taper tantrum, but staff might have become more cautious with communication in the

[15] I perform a Poisson regression of 1:00-3:59 ride volumes only on year-month, weekday and Manhattan activity controls and then subtract the fit levels from those observed.

wake of the late-2012 Medley leak. Absent additional collateral information, however, little can be concluded about the cause of the annual variation in drop-offs.

Late-night meetings might be scheduled to gather information about bond-market conditions. While the FOMC decides the scale of asset purchases, the distribution of purchases across maturities is the responsibility of the New York Fed. Bond markets are more opaque than stock markets, and the FRBNY might gather information about the supply of and demand for securities. Primary dealers are expected to provide market commentary to the New York Fed, and the New York Fed might seek information pertinent to the most recent announcement or to mooted plans as soon as they are permitted (Federal Reserve Bank of New York 2010a). All of the major commercial banks in the sample are also primary dealers except for BNY Mellon, and the primary dealers drive the results.

3.6 Overview of changes in coincidental drop-offs

Not all interactions between FRBNY insiders and commercial banks' insiders needs to occur at the New York Fed or at a major bank. People can, for example, chat informally over lunch, at a park or in a café. I employ coincidental drop-offs away from the New York Fed and the major financial institutions as noisy indicators of such informal meetings. In the interest of verbal economy, coincidental drop-offs will henceforth imply coincidental drop-offs that do not occur around any of the blocks where the New York Fed's or the major commercial banks' buildings are located.

For drop-offs to be considered coincidences, they must satisfy three spatial criteria and one temporal criterion. The first spatial criterion is that neither ride be mapped to the FRBNY or any of the other financial institutions. The second is that the drop-offs be mapped to the same census block. Since roads in New York City largely follow an approximately NS-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 Manhattan block along its shorter edge, 66 feet.[16] 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 within 10 minutes of each other.

[16] There are approximately 20 blocks to a mile along a Manhattan avenue, so a quarter of a block is approximately 66 feet (Pollak 2006)

One complication is that a single Fed drop-off may be coincidental with more than one drop-off from the major commercial banks or *vice versa*. Since the interest is in meetings and not individuals, I 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. Counts only include coincidences for which both drop-offs are in the specified intraday window, precluding, for example, a drop-off at 11:06 only coincidental with a drop-off at 10:58 from being counted in the 11:00-12:59 window.

Figure 3 Panel D presents summary statistics on the coincidental rides like those for direct rides. Given the filtration out of coincidences across window boundaries, I present summary statistics of bihourly windows rather than the previously used one-hour windows as before. Coincidental drop-offs are not particularly frequent, and the median for each window is 0. Mean coincidences peak at 0.47 between 8:00 and 10:00, slowly decline until the early evening, peak around 0.43 between 20:00 and 23:00 and then decline. The quantiles are fairly level except for the very early morning and 16:00-18:00, in which cases they are relatively low. As with direct rides, rides are clearly positively skewed, and there are no extreme outliers.

I again begin by examining variation during overlapping bihourly windows over the twelve event days around an FOMC meeting (Figure 7). The 2:00-3:59 through 4:00-5:59 windows are dropped due to a paucity of observations. I find several increases that are individually significant at the 1% confidence level, all of which occur during the blackout period: 0.25 on event day -7 between 20:00 and 22:00; 0.34 on event day -6 between 22:00 and 0:00; 0.29 on event day -5 between 8:00 and 10:00; 0.17 on event day -1 between 10:00 and 12:00; and 0.24 on event day $+1$ between 12:00 and 14:00. The increase on event day -6 is marginally significant at the 0.1% confidence level.

Coincidental drop-offs around noon are consistently and strikingly elevated from the day before the FOMC announcement onward. That starting point typically corresponds to the first day of an FOMC meeting and the day after the pre-FOMC discount-rate meeting. Moreoever, changes within a day of the FOMC announcement are statistically significant: an increase of 0.19 the prior day between 11:00 and 13:00 is individually significant at the 5% confidence level, and an increase of 0.24 the day after the announcement between 12:00 and 14:00 is individually significant at the

1% confidence level. A third individually significant lunchtime change is an increase of 0.16 on event +5 between 12:00 and 14:00. While the individual p-values for the noon increases are not very low, particularly given the number of changes examined, a potential increase in lunchtime meetings during a period for which Cieślak, Morse and Vissing-Jørgensen 2016 provide evidence of informal Federal Reserve communication motivates further examination.

3.7 Significance of the increase in lunchtime coincidental drop-offs

To assess the timing, magnitude and significance of the apparent increase in lunchtime coincidences in a more rigorous fashion, I undertake a similar data-mining exercise to that for the direct rides. I balance statistical and economic significance by choosing FOMC and intraday windows that minimise the average of the quantile of the specification by t-statistic and the quantile by extra rides. To assess significance conditional on the data mining, I again employ the Romano and Wolf (2005) StepM procedure. I first focus on windows around noon and let the data determine the span of event days during which rides are elevated. I consider the set of all contiguous FOMC windows of length 1 through 16 days between event days -8 and $+7$, and, in light of the elevated rides between 11:00 and 13:59, I consider the 11:00-12:59, 12:00-13:59 and the 11:00-13:59 windows. Thereafter, I seek further evidence that lunchtime coincidences are saliently and significantly elevated over the chosen FOMC window. I repeat the data mining exercise but this time expand the set of intraday windows to all two- and three-hour windows between 9:00 and 17:00, a span during which one might expect taxis to be largely occupied by individuals travelling for work purposes or on a break from work. In focusing only on the most significant intraday and event-day windows and only on parts of the day, I am again obtaining a lower bound on increases.[17]

Figure A.2 presents the spatial distribution of coincidental lunchtime drop-offs over the full set of lunchtime and event-day windows. While a significant fraction of coincidences occur in areas with a high concentration of lunchtime destinations such as restaurants and shops – *e.g.*, TriBeCa, SoHo and the Meatpacking District (roughly the southwestern part of Chelsea/Flatiron/Union Square/Hudson Yards) – there is a large cluster at Penn Station and, to a lesser degree, Grand Central Terminal. Given the high volume of passenger traffic at these transit hubs, any drop-

[17] Jointly data mining the full set of intraday and event-day windows was computationally impractical, and achieving identification away from working hours for coincidental drop-offs would be more challenging.

off near them could have a high probability of being coincidental with a drop-off from a major commercial bank. Consequently, in the baseline specification, I omit coincidences at those hubs and, so as not to capture spillover, from the adjacent blocks as well. Coincidental drop-offs at other unlikely spots for meetings such as hospitals are also present, but a block-by-block assessment of likely and unlikely meeting spots would be a slippery slope. A number of the coincidences occur in the vicinities of hotels and may include unrelated returns to hotel rooms, but these would have to vary systematically around lunchtime around meetings in Washington, D.C. to do more than to add noise.

With the baseline specification, lunchtime coincidences are most significantly elevated from one day before the FOMC announcement through seven afterwards and between 11:00 and 14:00. I find an increase of 1.15 coincidences (+43.8%) over this window, and the individual p-value is less than 0.001 (Table 3 Column i). The p-value is less than 0.05 when the conservative data-mining-robust calculation is employed. On no date during an FOMC window does the coincidence count exceed 3, so the result is not driven by a large outlier. The subsequent restriction of the FRBNY pick-ups to the vicinity of the headquarters yields the same windows, a slightly larger increase and greater significance (Column ii, the conservative specification): 1.16 extra rides (+49.7%), an individual p-value less than 0.001 and a data-mining-robust p-value of less than 0.01. The increase in lunchtime coincidences is thus completely driven by pick-ups in the vicinity of 33 Liberty Street and the main entrance of 33 Maiden Lane and not by the businesses and residences to the Northeast and East of 33 Maiden Lane. In light of this result, I focus on the conservative specification.

Midtown and the Financial District have a high concentration of financial firms and highrises, so coincidental drop-offs there might reflect the conduct of unrelated business at nearby premises. Additionally, Figure A.2 shows small clusters of coincidences at Weill Cornell Medical Center, Helmsley Medical Tower, NYU Langone and Bellevue, and hospitals are unlikely places to meet for lunch. When coincidences in these neighbourhoods and hospitals are dropped from the conservative specification, the selected windows change slightly to event days -2 through $+6$ and 11:00-12:59 (Column iii). The percentage increase more than doubles to 103.5%, while the change in rides only falls by about a third to 0.77. The individual p-value remains less than 0.001, and the data-mining-robust one is again less than 0.01. These results together with the large number of rides in dining and shopping areas further bolster the proposition that the variation in coincidences largely reflects variation in informal lunchtime meetings.

I now show that the key results are not dependent on a tight focus on lunchtime. When I employ the conservative specification and impose an intraday window of 9:00 up to 17:00 that should largely capture non-commute rides to and from workplaces, a nearly identical FOMC window is selected: -2 through $+7$. The increase over that full span is 1.58 rides (+22.2%), indicating that the extra rides at lunch are additional rides during the work day, not an intraday shift (Column *iv*). This increase is significant at the 1% confidence level individually and at the 5% confidence level when the data-mining is conservatively accounted for. When I allow any two- or three-hour window from 9:00 through 16:59, the same FOMC window and the 10:00-12:59 intraday window are selected. Even with the large number of additional models, the increase of 1.41 rides (+49.8%) is significant at the 1% confidence level when the data mining is accounted for (Column *v*). While this window begins well before one might presume lunch would start, over 80% of the increase occurs between 11:00 and 12:59, and that change is significant at a conventional level (Column *vi*).

While information can flow whenever individuals are close, an obvious question is whether the additional coincidental drop-offs reflect planned meetings. To help to answer this question, I filter rides from the New York Fed and the major commercial banks by passenger count. Where there are multiple passengers, those passengers might be going for lunch together and only incidentally find themselves near individuals who arrived from the FRBNY or the major commercial banks. Fed staff might, for instance, go for lunch or to a park together after their work in support of FOMC meetings has been completed, and I might be picking up nothing more than a similar taste in restaurants or leisure activities to other bankers'. In the interest of increasing the signal-to-noise ratio, I remove such cases by restricting the sample of rides from the New York Fed and the major commercial banks to those for which only a single passenger is indicated. One caveat is that unlike the GPS coordinates and times of pick-ups and drop-offs, passenger count is reported by drivers (NYC Taxi & Limousine Commission 2015). While there may be inaccuracies, it would seem mostly likely that they would be largely white noise, and even systematic under- or overreporting of singletons would not necessarily be a serious threat to identification. The fare structure over the period was not an explicit function of the number of passengers, and there appears to be no incentive to misreport the count in any consistent way (NYC Taxi & Limousine Commission 2012, Flegenheimer 2012).

The significance and magnitudes of the increases in coincidental drop-offs of single passengers inspire greater confidence that lunchtime coincidental drop-offs largely reflect planned meetings. Columns *vii* through *xii* of Table 3 replicate Columns *i* through *vi* but with only one passenger in each taxi. For the working-day specifications, the selected windows are identical to those where there is no filtration on passenger count, and one observes that single-passenger coincidences contribute about four-fifths of the total increase in coincidences (Columns *x*, *xi* and *xii* compared with *iv*, *v* and *vi*). With a focus only on lunchtime, the FOMC window is wider, from event day -8 through $+7$ (Columns *vii*, *viii* and *ix* compared with *i*, *ii* and *iii*). Across all specifications, increases in percentage terms are uniformly greater than when passenger count is unrestricted. The estimates of extra rides are similar, though the average count per day is unsurprisingly generally lower for the single-passenger coincidences. Statistical significance is mostly greater for single-passenger rides, and the changes are uniformly significant at at least the 5% confidence level when one accounts for data mining.

As with rides to the New York Fed, 2012 contributes importantly to the increase in lunchtime coincidental drop-offs. Figure 6 Panel B plots the average count of unexplained coincidences during a significance-maximising FOMC window for each year from 2009 through 2014. The residuals are obtained from Poisson regressions with just the period and taxi-activity controls over the significance-maximising intraday window.[18] For both the conservative specification and the single-passenger conservative specification, the mean residuals are positive each year, though trivially so in 2009. Without filtration by passenger count, the unexplained rides per FOMC meeting hover around 0.65 except in 2012, in which case they reach 1.97. With only single passengers, the residuals steadily grow until they reach 1.64 in 2012 and then steadily decline. While the synchronicity of high residuals suggests a link to information seeking about changes in monetary policy such as the adoption of a formal inflation target or the third round of quantitative easing, again nothing can be concluded about the motivation without collateral data.

Despite the highly statistically significant evidence in support of an increase in lunchtime meetings, little can be concluded about who is travelling from the vicinity of the New York Fed or what their rôles at or their connexions to the Fed might be. The regular observation of potential return taxi trips would support identification with individuals based at the main FRBNY premises, but

[18] More precisely, I obtain for each year the average residual on days in the significance-maximising FOMC window and multiply that average by the typical number of weekdays over that window.

even with liberal matching criteria, fewer than 20% of coincidences can be linked to a ride with a drop-off at the New York Fed (Table A.5). It is possible that taxis are taken when punctuality is more important, and more economical options like public transportation are taken on the way back. Alternatively, and in light of travel time, meetings might be stops on the way to other locations.

3.8 Robustness checks for the increase in lunchtime coincidental drop-offs

The statistical and economic significance of the changes obtained from data mining are robust to variations in window selection. Table 4 presents evidence that the finding of increased lunchtime coincidences is not fragile with respect to the choice of FOMC and intraday windows, both in the case of rides that are not filtered by passenger count (Columns *i* through *iii*) and singleton coincidences (Columns *vii* through *ix*). The data-mining-robust significance is based on examination of all lunchtime and FOMC windows. The first pre-specified windows capture the maximal lunchtime set: event days -8 through $+7$ and 11:00 through 13:59. The second is the intersection of the windows obtained from lunchtime data mining: event days -1 through $+6$ and 11:00 through 12:59. Finally, I restrict that narrower set of windows to the particularly sensitive period from event day -1 through $+1$, the typical start of an FOMC meeting through the end of the blackout window. Day counts for these windows and their shares in the full sample are presented in Table A.3. The estimates with the conservative specification are all individually significant at the 1% confidence level except for the maximal window for any passenger count, in which case the p-value is 0.016, and are mostly significant at the 0.1% confidence level. When one accounts for data mining over the lunchtime windows, all of the changes are significant at the 5% confidence level except for the maximal window with any passenger count. The maximal and intersectional windows yield increases that are largely comparable to those obtained with data mining but are generally lower. 0.51 extra coincidences are observed during the one-day window around the FOMC meeting between 11:00 and 13:00 (Column *iii*), 0.35 of which are singleton coincidences (Column *ix*). Figure 6 Panel C repeats the examination of coincidences unexplained by the time and Manhattan taxi-activity controls but for the 11:00-12:59 window within a day of an FOMC announcement. While 2012 was an important driver of the estimated increase in coincidental drop-offs for the wider window, it is overwhelmingly responsible for that between the typical start of the FOMC meeting until the end of the blackout.

Adjustments to the vertex shifts do not overturn the key findings. I repeat the lunchtime data-mining exercise for the conservative specification with shifts of 50 and 150 feet both for any passenger count and for singletons. In all four cases, the individual p-values are below 0.001, and the robust p-values are below 0.01 (Columns *iv*, *v*, *x* and *xi*). With a reduction to 50 feet, the selected FOMC windows are slightly shorter in length but continue to span the FOMC meeting, and the intraday windows are all 11:00-12:59 (Columns *iv* and *x*). The changes in percentage terms roughly double, but the estimated increases in absolute terms fall to about 0.6 coincidences. When the expansion is increased to 150 feet, the percentage changes fall somewhat, while the change in units of coincidences rises to 1.44 for all passenger counts and 1.35 for singletons (Columns *v* and *xi*). These higher values suggest the expansion by 100 feet might yield conservative estimates.

I obtain broadly similar results when I choose the windows that yield the highest t-statistic. The conservative specification with any passenger count yields windows from event day -1 through event day +6 and 11:00-12:59 (Column *vi*), and the conservative specification with singletons yields windows of event day -1 through +7 and 11:00-12:59 (Column *xii*). With the shorter windows, the estimated increases in coincidences fall to 0.95 and 0.85.

The results for lunchtime coincidences are not fragile with respect to the choice of covariates and clustering. Column *i* of Table 5 shows that very little changes when I drop the Manhattan taxi volume from the conservative specification. When I drop the year-month and weekday indicators and employ White standard errors, the estimate of additional rides falls to 0.97 but still has an individual p-value below 0.001 and is significant at the 5% confidence level when data-mining is accounted for (Column *ii*). The selected window increases by a day, and the intraday window shrinks to 11:00-12:59. I find that the omission of coincidences at transit hubs primarily served to reduce noise. When I broaden the scope of the less-restrictive baseline specification to include coincidental drop-offs at transit hubs, the same FOMC window is selected, but the intraday window becomes 11:00-12:59 (Column *iii*). The increase in rides is similar at 0.98, but the individual and data-mining-robust p-values rise non-trivially to 0.004 and to greater than 0.1.

The results are robust to variation in the definition of a coincidence. When I decrease the maximum spatial distance to 1/8 of a block for the conservative specification, the estimated increase falls in units of rides to 0.58, rises in fractional terms to 76.9% and remains significant at a conventional level both individually and when the multiple comparisons are accounted for (Column *iv*).

The selected event span does, however, change non-trivially to event day -7 through $+6$, and the intraday span shrinks to 11:00-12:59. With the same maximum distance of 1/8 of a block but with a maximum time interval of 20 minutes, I find a larger increase in rides, similar significance and the selection of an FOMC window spanning event days -1 through $+7$ (Column *v*). Modifying the conservative specification by increasing the maximum interval to 20 minutes yields similar windows but a smaller change in rides of 0.89, a percentage change about 50% lower in magnitude and only individual significance at a conventional level (Column *vi*). The combination of a comparable change in units of coincidences, a large fall in percentage terms and a loss of significance suggests that the extra time mostly adds noise.

When I repeat the exercise for the singleton coincidences, the individual and data-mining-robust p-values are all less than 0.001 and 0.05 respectively except when the maximum spatial and temporal separations are 1/4 of a block and 20 minutes (Table 5 Columns *vii* through *xii*). In that case, the change is highly individually significant but insignificant conditional on data mining. The windows are generally very similar to those obtained with the unmodified conservative specification with single passengers, though the intraday windows are longer when a maximum distance of 1/8 of a block is used, and the FOMC window is shorter when the maximum temporal separation is 20 minutes. Appendix A.1 demonstrates the robustness of lunchtime increases in coincidences to changes in the sample period, changes in how rides are mapped to institutions and the use of OLS with simple standard errors and asymptotic p-values. Also presented in Appendix A.1 are placebo tests that demonstrate the peculiarity of the lunchtime increases to periods around FOMC meetings.

4 Discussion

Highly statistically significant patterns in New York City yellow taxi rides suggest that opportunities for information flow between individuals present at the New York Fed and individuals present at major commercial banks increase around FOMC meetings. Their geography, timing and passenger counts are consistent with an increase in planned meetings causally linked to the incidence of monetary-policy activities.

Causality need not reflect a mutual desire to communicate about monetary-policy matters beyond what has been widely disseminated. Meetings both during and after the blackout could be purely social engagements or discreet Fed information gathering regarding bond-market conditions pertinent to the implementation of monetary policy, but sensitive information could still flow accidentally. Federal Reserve staff who broadly restrict their interactions with outside parties during the blackout could address pent-up demand by scheduling an above-average volume of meetings in the days after its end. Consequently, while the blackout may reduce the risk of leakage of preparations for FOMC meetings, it may also increase opportunities for outside parties to gain insights into their still-confidential proceedings and support material over the following days.

The approximately 1.6 additional meetings around an FOMC announcement inferred here might seem like a small increase, but a low absolute value should not be confused with insignificance. Even if the taxi data reflected the entire variation of interactions between the Fed and the financial institutions, it would not follow that that the opportunity for information flow would necessarily be of completely trivial importance for financial firms and information flow into markets. Even the occasional insight into non-public Federal Reserve data and discussions provided accidentally by an unwitting New York Fed asset could be highly profitable, and accidents of history like insiders' social ties or close working relationships could give some firms an advantage over competitors around FOMC meetings.

Taxis are, of course, not the only means by which individuals can interact; the American G-SIBs are only a subset of New York's financial institutions; New York is not the only city where sensitive Federal Reserve data may be obtained, and I have not even fully mined the taxi data. The large increases in percentage terms and their high statistical significance suggest a broader increase in major commercial banks' interactions with the Federal Reserve. At the same time, one must take care not to over-extrapolate. Even the full set of extra interactions around FOMC meetings might involve a fairly small number of individuals who are not representative of the Federal Reserve System broadly, and the data can at most provide evidence of an increase in opportunities for information flow.

The timing of the increases at lunch and very late at night together with the apparent meeting locations fit with the speculation of systematic and informal information flow that Cieślak, Morse and Vissing-Jørgensen (2016) obtain from asset-price movements and anecdotes. Cieślak, Morse and Vissing-Jørgensen (2016) find particularly high average excess returns on S&P 500 futures over a window dubbed week 0 that translates approximately to event days -1 through $+5$ (Table A.2). With a complementary appeal to media reports and Federal Reserve transcripts, they suggest that Fed leakage during informal communication is responsible. This window lies in the middle of the span during which I found FRBNY interactions with outside parties to be significantly elevated. This coincidence is by no means proof of the mechanism proposed for the excess returns, but this paper's results are congruous with the inference of regular informal communication obtained by alternative means.

There is, however, a discrepancy between the intraweek timing of news flow to markets argued in Cieślak, Morse and Vissing-Jørgensen (2016) and of the meetings that I infer. Using returns on S&P 500 futures, Cieślak, Morse and Vissing-Jørgensen (2016) posit that market-moving Federal Reserve leakage since 1994 has mostly occurred in the run-up to the FOMC announcement; however, using taxi rides from 2009 through 2014, I find that the most significant increases in New York meetings occur afterwards. If the inference in Cieślak, Morse and Vissing-Jørgensen (2016) is valid for my sample period, the extra meetings on which I have focused would generally not be particularly important conduits of Federal Reserve news to financial markets. It is certainly conceivable, however, that individuals could trade profitably on insights into the Federal Reserve without driving market movements of the magnitude that Cieślak, Morse and Vissing-Jørgensen (2016) present. The non-trivial market responses to the release of FOMC minutes is a testament to the dollar value of insights into an FOMC meeting that remains even weeks after the associated announcement, not to mention days (Nechio and Wilson 2016, Rosa 2013). A party with access to firms' trades could test the relationship between inferred meetings with Fed insiders and market activities, but I am unable to undertake this examination.

Questions of interpretation and of what constitute meaningful results and convincing identification are naturally raised by the introduction of new methods. These data capture a vast amount of business and leisure activity, and this paper is but a first pass at their exploitation to gain insight into institutional behaviour. There are without doubt rough edges in my empirical work and analysis, and the refinement of tools and frameworks with which to understand these micro data could be of significant value to many studies in economics and finance.

The microlevel behaviour that can be gleaned from mobility data also has implications outside of academia. As demonstrated here and elsewhere, the absence of explicit identifiers does not guarantee anonymity, and mobility data raise privacy concerns (*e.g.*, Golle and Partridge 2009, Giannotti and Pedreschi 2008 and Hicks and Srivatsa 2012). Even if institutions and individuals are extremely cautious in guarding their own movements and in controlling the usage of data on themselves, insights into their activities can still be obtained from the movements of those with whom they interact. Further studies on what can be inferred from mobility data can yield a social dividend in the identification of data features that should be treated as personally identifiable information, in the development of stronger anonymisation and in guidance on how individuals and firms can guard themselves against the exploitation of their movements.

5 Conclusion

I employ a rich dataset constructed from anonymous trip-level taxi data to examine interactions between insiders of the Federal Reserve Bank of New York and major commercial banks around FOMC meetings. I find evidence suggestive of an increase in meetings between them both at the New York Fed's offices and in areas associated with dining and shopping. The occurrence of the changes very late at night and during typical lunch hours suggests informal or discreet communication. This first pass at what insights taxi data can provide into opportunities for information flow from the Federal Reserve Bank of New York to major commercial banks illustrates the potential of ride data as a tool for the examination of individual and corporate behaviour.

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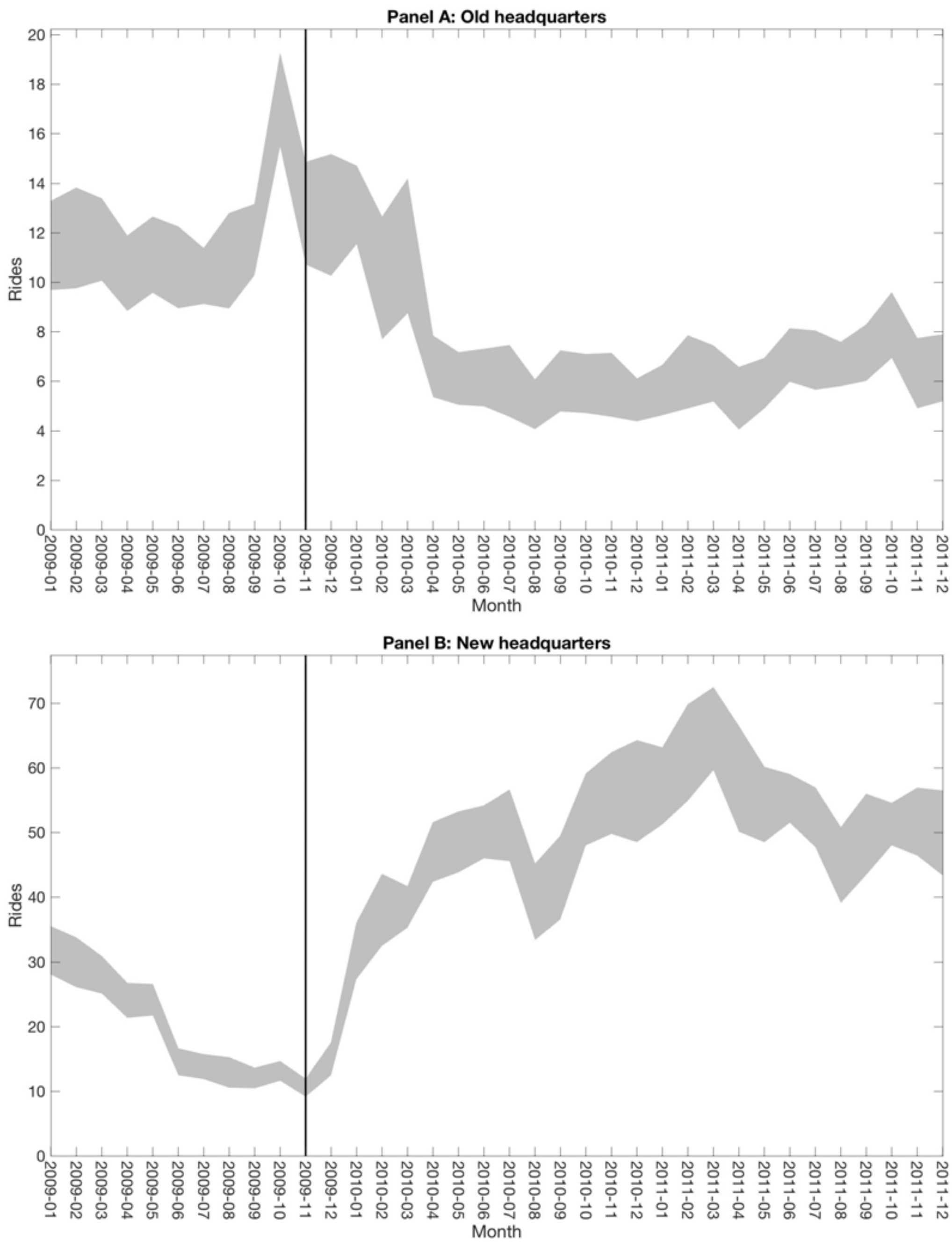
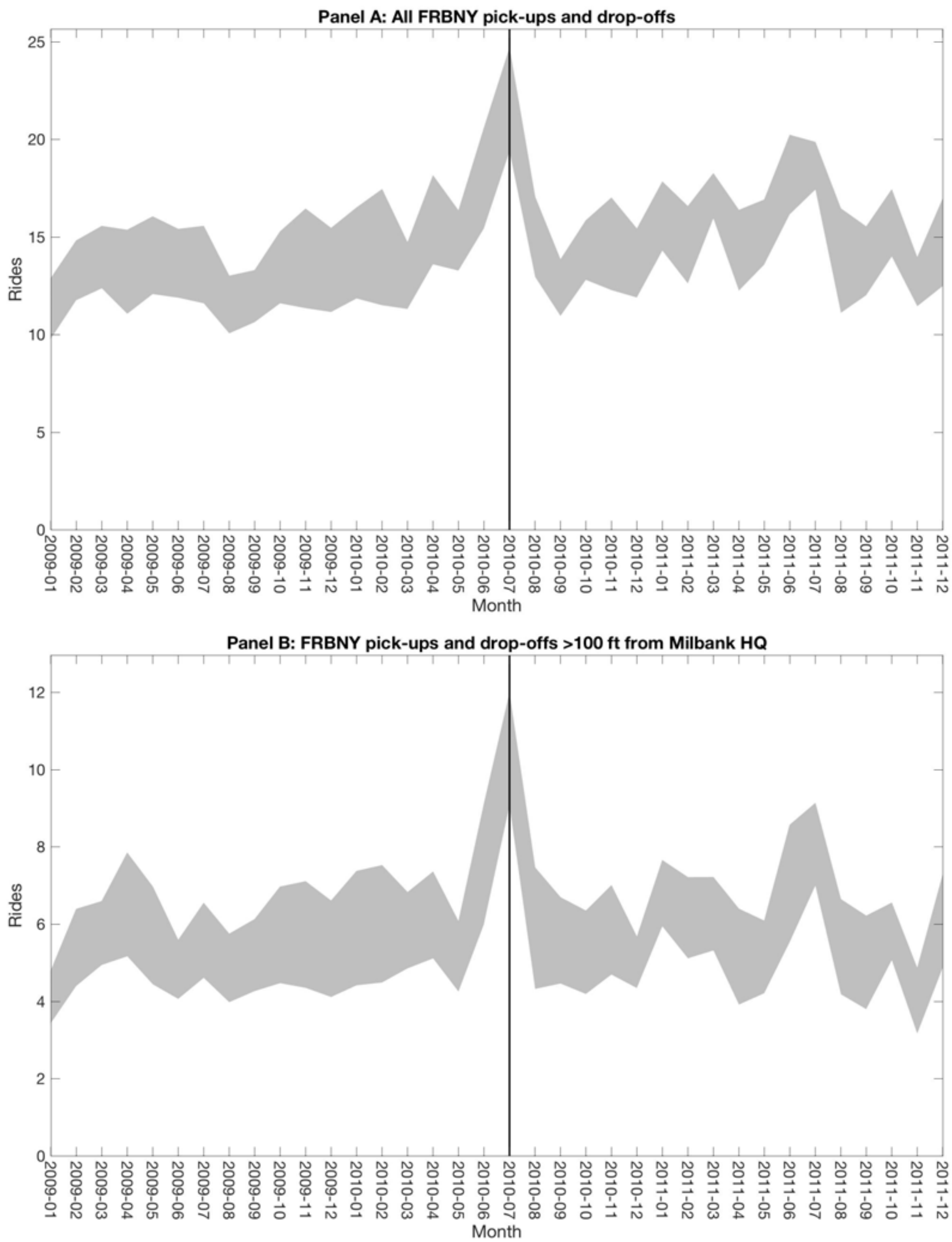
Figure 1: Two-deviation confidence bands around mean weekday rides between Goldman Sachs headquarters and other major commercial banks



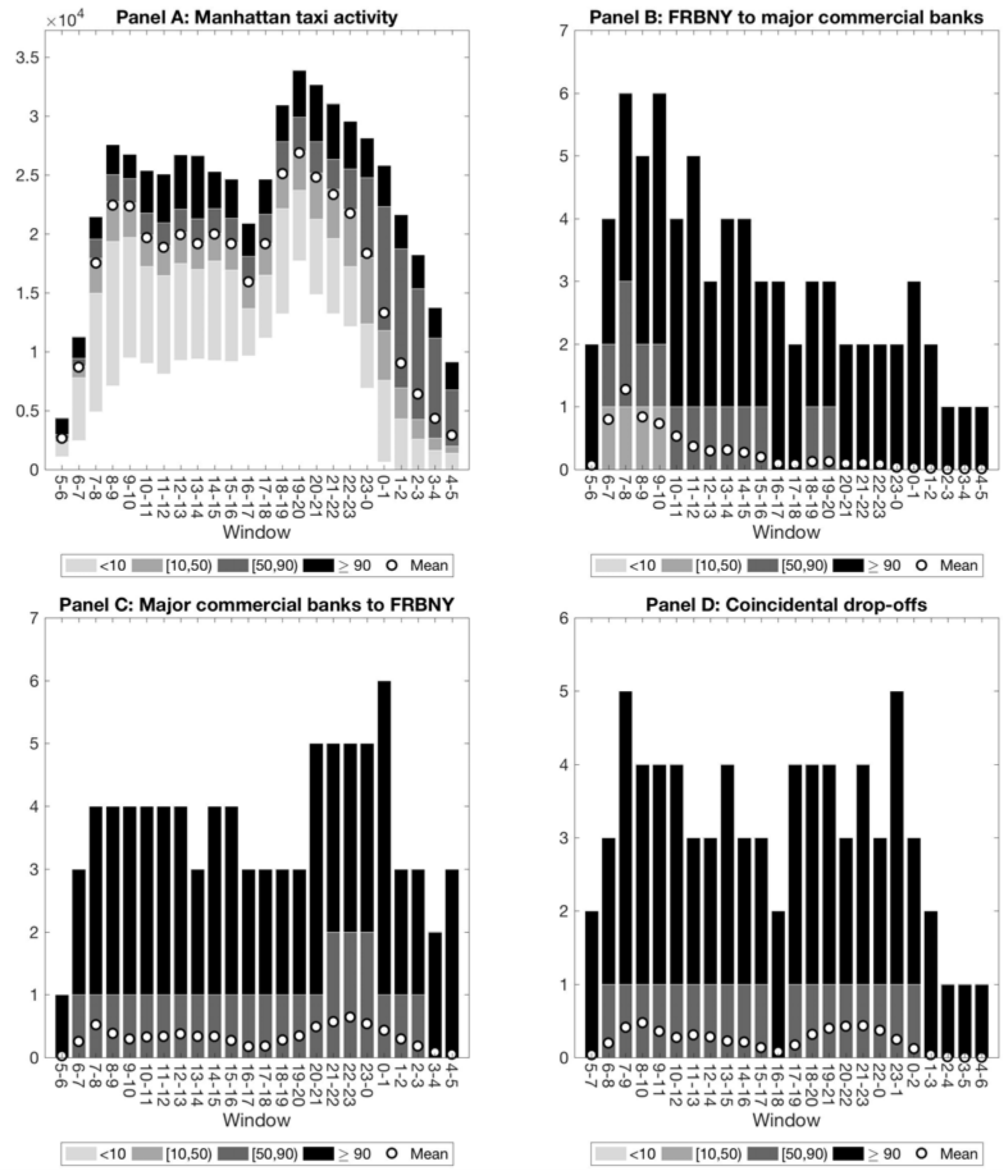
Notes: The vertical bar indicates the commencement of Goldman Sachs's staff relocation in November 2009. A day spans the period from 5:00 to 4:59 the next morning.

Figure 2: Two-deviation confidence bands around mean weekday rides between the FRBNY and major commercial banks



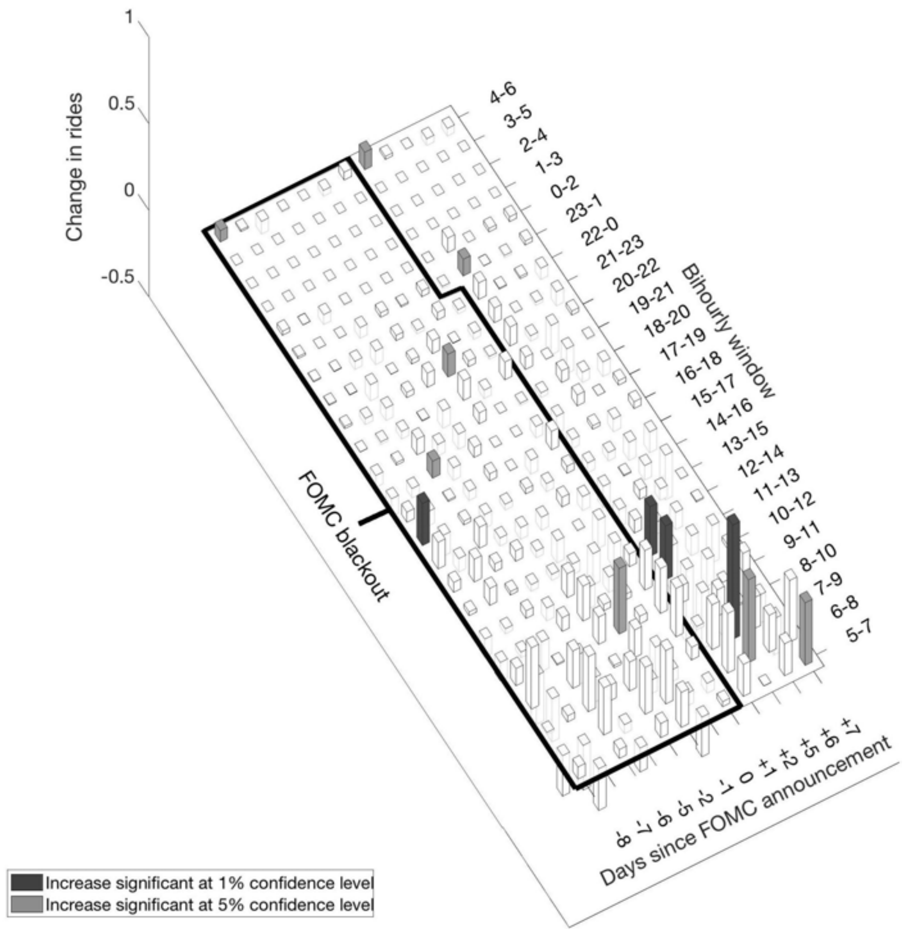
Notes: The vertical line marks the signing of Dodd-Frank into law in July 2010. A day spans the period from 5:00 to 4:59 the next morning.

Figure 3: Means and quantiles of weekday rides



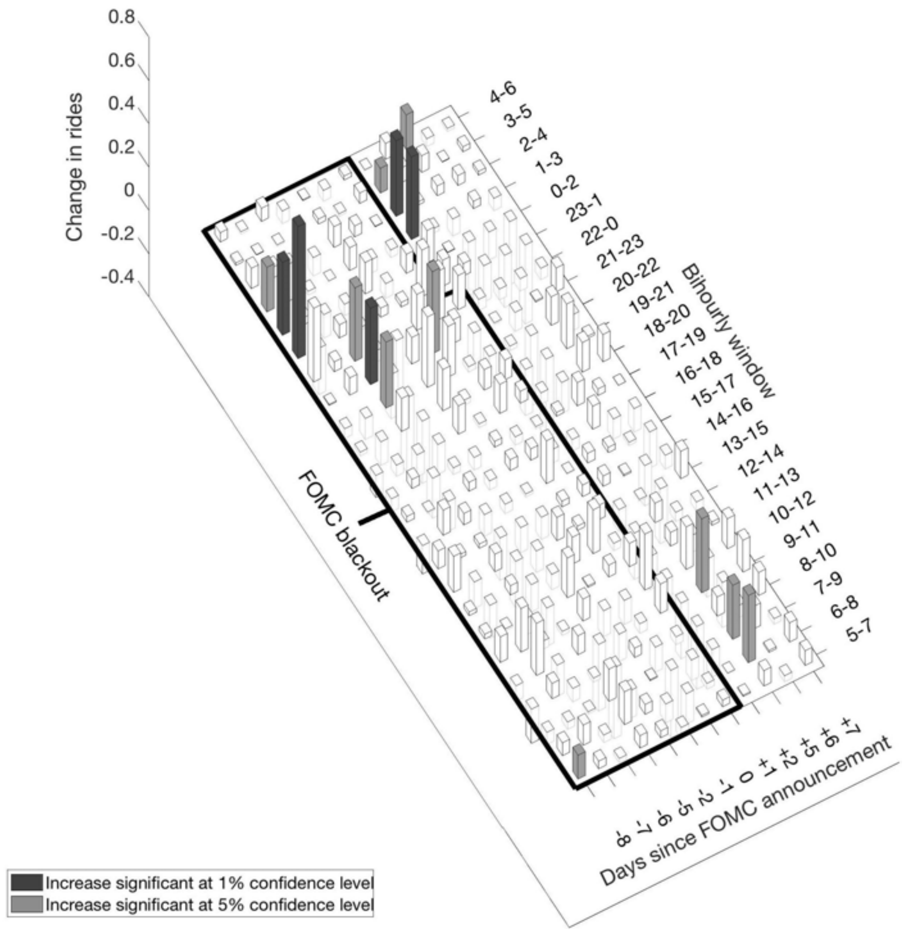
Notes: The sample spans 1425 weekdays from the beginning of 2009 through the end of 2014. Intraday windows starting from 0:00 up to 4:00 are mapped to the previous calendar day. Panel A: the mean of pick-ups and drop-offs of intra-Manhattan yellow-taxi rides. Panel B: yellow taxi rides from FRBNY buildings to the sample of locations where major commercial banks have substantial front-office presences. Panel C: yellow taxi rides from the sample of locations where major commercial banks have substantial front-office presences to FRBNY buildings. Panel D: baseline coincidental drop-offs during bihourly windows of rides originating around New York Fed buildings and locations where major commercial banks have substantial front-office presences.

Figure 4: Changes in rides from the FRBNY to the major commercial banks around an FOMC meeting



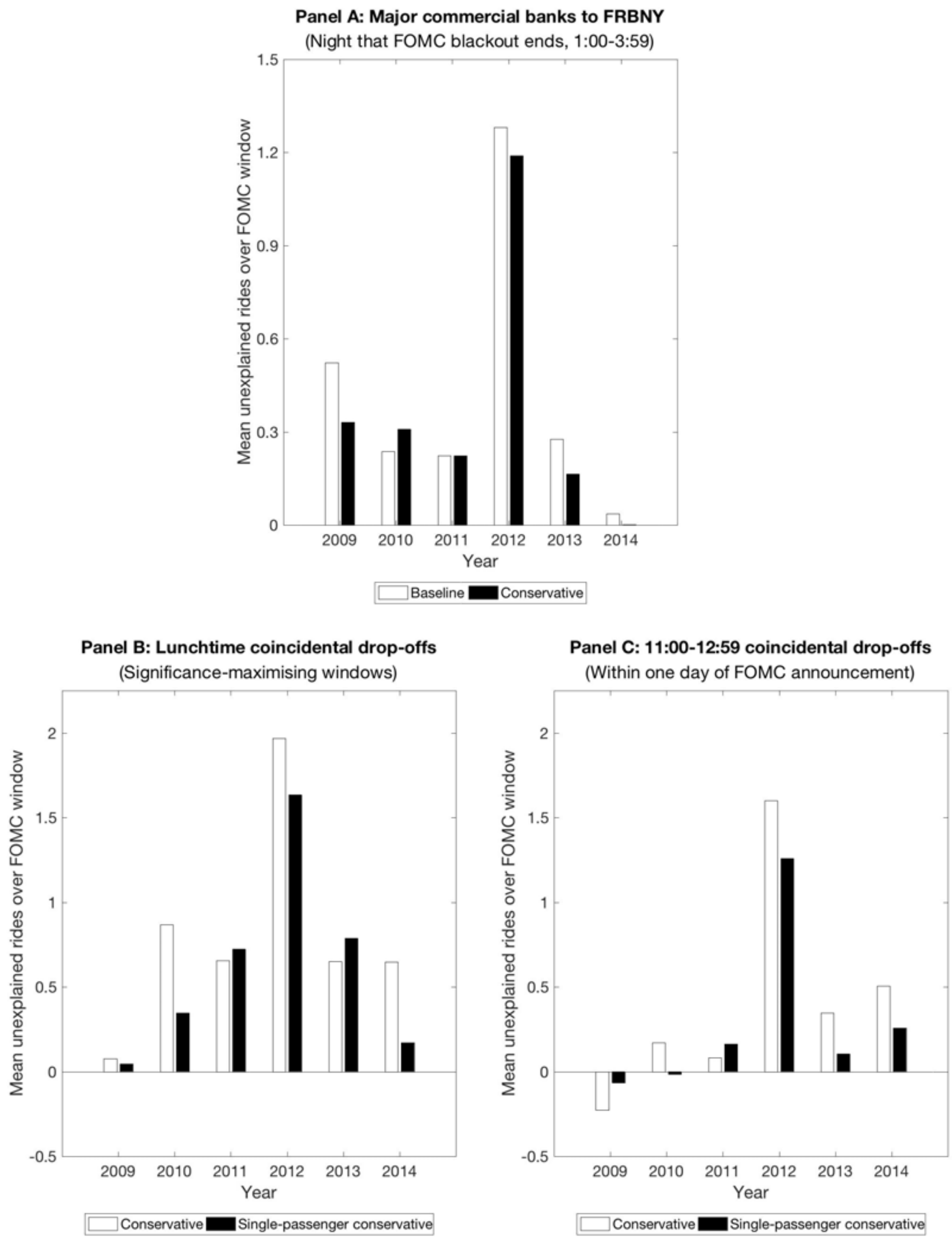
Notes: A separate Poisson regression is run for each intraday-window-event-day pair, where event day t is an offset of t calendar days from the FOMC announcement. For greater consistency with typical work days, windows beginning up to 4:00 are treated as part of the previous calendar day. The intensity of the rides is given by Eq. 1. Year-month fixed effects, weekday indicators and overall Manhattan taxi activity are used as controls. Changes in rides are average partial effects. 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 10000 repetitions and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation.

Figure 5: Changes in rides from the major commercial banks to the FRBNY around an FOMC meeting



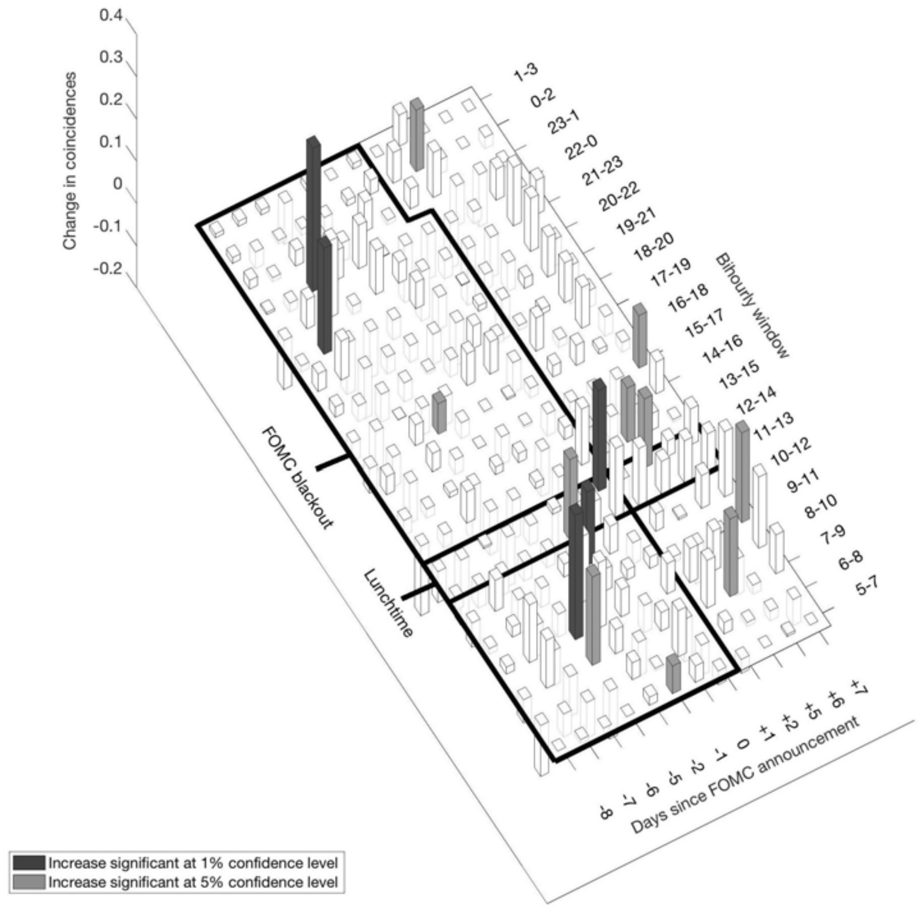
Notes: A separate Poisson regression is run for each intraday-window-event-day pair, where event day t is an offset of t calendar days from the FOMC announcement. For greater consistency with typical work days, windows beginning up to 4:00 are treated as part of the previous calendar day. The intensity of the rides is given by Eq. 1. Year-month fixed effects, weekday indicators and overall Manhattan taxi activity are used as controls. Changes in rides are average partial effects. 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 10000 repetitions and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation.

Figure 6: Assessment of individual years' contributions to the estimated increases in rides



Notes: Rides are regressed only on year-month fixed effects, weekday controls and overall Manhattan taxi activity, and the mean total unexplained rides over the each year's FOMC windows is plotted. More precisely, I obtain for each year the average residual on days in the significance-maximising FOMC window and multiply that average by the typical number of weekdays over that window. A larger mean is suggestive of a greater contribution to the estimated increase over the FOMC window for the full sample. The coincidental drop-offs occurred between 11:00 and 14:00. The significance-maximising FOMC window for the baseline specification spans the day before the FOMC announcement through one week afterward, while that for the single-passenger conservative specification spans event days eight days before the announcement through seven afterwards, while the intraday windows are respectively 11:00-13:59 and 11:00-12:59.

Figure 7: Changes in coincidental drop-offs around an FOMC meeting



Notes: Classification of rides originating around the New York Fed and a major commercial bank as coincidental drop-offs requires the two rides to be mapped to the same census block, to be within 1/4 block along the NS and EW axes and to be separated by no more than 10 minutes. The baseline specification is employed where rides may originate in the vicinity of either FRBNY building, and coincidental drop-offs around transit hubs, the New York Fed and the major commercial banks are ignored. 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 the FOMC announcement. For greater consistency with typical work days, windows beginning up to 4:00 are treated as part of the previous calendar day. The intensity of the coincidences is given by Eq. 1. Year-month fixed effects, weekday indicators and overall Manhattan taxi activity are used as controls. Changes in rides are average partial effects. One-sided p-values for the coefficients with t-statistics of at least 1.25 are obtained from pairs bootstrapping of year-month observations with at least 10000 repetitions and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation. The 2:00-3:59 through the 4:00-5:59 windows are omitted due to a paucity of observations.

Table 1: Ride volume between the New York Fed and major commercial banks around Dodd-Frank milestones

Panel A: Quantile and count of direct rides between FRBNY and major commercial banks

Dodd-Frank Milestone	Date	Prior weekday	Date of	Next weekday
Introduced in House	2 December 2009	87.6% (19)	5.8% (7)	62.7% (15)
Passed in House	11 December 2009	21.6% (10)	70.7% (16)	70.7% (16)
Passed with amendment in Senate	20 May 2010	62.7% (15)	29.3% (11)	54.7% (14)
Conference report filed	29 June 2010	99.7% (29)	99.8% (30)	54.7% (14)
Conference report agreed in House	30 June 2010	99.8% (30)	54.7% (14)	54.7% (14)
Conference report agreed in Senate	15 July 2010	100.0% (35)	70.7% (16)	96.1% (22)
Signed by President	21 July 2010	99.9% (34)	96.1% (22)	91.3% (20)

Panel B: Quantile and count where FRBNY pick-ups and drop-offs $>$ 100 *feet from Milbank HQ*

Dodd-Frank Milestone	Date	Prior weekday	Date of	Next weekday
Introduced in House	2 December 2009	92.2% (9)	10.6% (2)	78.7% (7)
Passed in House	11 December 2009	37.0% (4)	52.7% (5)	37.0% (4)
Passed with amendment in Senate	20 May 2010	37.0% (4)	22.3% (3)	52.7% (5)
Conference report filed	29 June 2010	99.2% (13)	98.5% (12)	22.3% (3)
Conference report agreed in House	30 June 2010	98.5% (12)	22.3% (3)	52.7% (5)
Conference report agreed in Senate	15 July 2010	99.9% (15)	78.7% (7)	95.6% (10)
Signed by President	21 July 2010	98.5% (12)	92.2% (9)	78.7% (7)

Notes: For greater consistency with working days, daily ride volume is calculated as rides from 5:00-4:59. The quantiles are calculated over the 1425 weekdays in the filtered sample spanning 2009 through 2014.

Table 2: Poisson regression analysis of rides from major commercial banks to the New York Fed around FOMC meetings

Candidate windows:	*Individual event days −8 through +7 × all intraday windows*											
	i	*ii*	*iii*	*iv*	*v*	*vi*	*vii*	*viii*	*ix*	*x*	*xi*	*xii*
	Windows yielding the most significant increase in rides											
First event day of FOMC window	+1	+1	+1	−1	+1†	+1	+1	−8	+1†	+1	+1	+1
Last event day of FOMC window	+1	+1	+1	−1	+1†	+1	+1	−8	+1†	+1	+1	+1
Start of intraday window	1:00	1:00	1:00	20:00	1:00†	1:00	1:00	23:00	1:00†	1:00	1:00	1:00
End of intraday window	3:59	3:59	3:59	22:59	3:59†	3:59	3:59	1:59	3:59†	3:59	3:59	3:59
	Change in rides from major commercial banks to FRBNY during FOMC window											
Partial effect (%)	108.6**	120.8**	120.5**	50.8**	98.0**	149.9**	189.5**	41.4**	47.3**	64.6**	108.6**	120.8**
t-statistic	(4.84)	(4.50)	(4.50)	(3.85)	(3.63)	(4.43)	(4.48)	(3.57)	(2.60)	(3.17)	(4.84)	(4.50)
Extra rides per FOMC window	0.50	0.43	0.43	0.68	0.39	0.34	0.32	0.86	0.41	0.43	0.50	0.43
Individual p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.009	0.003	<0.001	<0.001
Data-mining-robust significance	0.001	0.01	0.01	0.05	0.1	0.01	0.01	0.1	>0.1	>0.1	0.001	0.01
Vertex shift (feet)	100	100	100	100	100	50	50	150	150	150	100	100
Only main FRBNY building		•	•	•	•		•			•		•
Control for Manhattan activity	•	•				•	•	•	•	•	•	•
Weekday controls	•	•	•			•	•	•	•	•	•	•
Year-month FE, clustering	•	•	•			•	•	•	•	•	•	•
White standard errors				•	•							
Significance-maximising windows	•	•	•	•		•	•	•		•		
t-statistic-maximising windows											•	•
Pseudo-R^2	0.21	0.19	0.19	0.01	0.01	0.18	0.17	0.32	0.24	0.19	0.21	0.19
Observations	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425
Number of candidate models	576	572	572	572	572	575	569	576	576	576	576	572

Notes: Rides are modelled as Poisson processes with intensity given by Eq. 1, and the count of extra rides over the FOMC window is the associated average partial effect times the typical number of weekdays during the window. The set of event days examined are the offsets from an FOMC announcement between −8 and +7 days that typically fall on weekdays. Individual p-values are right-tail quantiles, are obtained from pairs bootstrapping at the year-month level with 100000 simulations and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation. Data-mining-robust significance is obtained using the Romano and Wolf (2005) StepM procedure, and details are provided in Appendix A.4. Counts of candidate windows can vary across specifications due to variation in data sparsity. Regressions span a filtered set of weekdays from 2009 through 2014. Windows beginning from 0:00 through 4:00 are treated as part of the preceding calendar day. Table A.4 provides additional definitions.
**/* indicates individual significance at the 1%/5% confidence level. † indicates a pre-specified window parameter.

Table 3: Poisson regression analysis of coincidental drop-offs of rides originating at the FRBNY and rides originating at major commercial banks around FOMC meetings

Passenger count:	*Any number*						*Singletons*					
Candidate windows:	*All FOMC × lunchtime*			*All FOMC × working day*			*All FOMC × lunchtime*			*All FOMC × working day*		
	i	*ii*	*iii*	*iv*	*v*	*vi*	*vii*	*viii*	*ix*	*x*	*xi*	*xii*
	Windows yielding the most significant increase in coincidental drop-offs											
First event day of FOMC window	−1	−1	−2	−2	−2	$-2^{\dagger}$	−8	−8	−8	−2	−2	$-2^{\dagger}$
Last event day of FOMC window	+7	+7	+6	+7	+7	$+7^{\dagger}$	+7	+7	+7	+7	+7	$+7^{\dagger}$
Start of intraday window	11:00	11:00	11:00	9:00†	10:00	11:00†	11:00	11:00	11:00	9:00†	10:00	11:00†
End of intraday window	13:59	13:59	12:59	16:59†	12:59	12:59†	12:59	12:59	12:59	16:59†	12:59	12:59†
	Change in coincidental drop-offs during FOMC window											
Partial effect (%)	43.8**	49.7**	103.5**	22.2**	49.8**	61.3**	79.4**	94.1**	120.2**	33.2**	87.7**	106.3**
t-statistic	(3.45)	(3.83)	(4.18)	(3.20)	(4.35)	(3.54)	(3.88)	(4.08)	(3.95)	(2.96)	(5.18)	(4.15)
Extra rides per FOMC window	1.15	1.16	0.77	1.58	1.41	1.14	1.18	1.22	0.75	1.25	1.25	0.93
Individual p-value	<0.001	<0.001	<0.001	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.003	<0.001	<0.001
Data-mining-robust significance	0.05	0.01	0.01	0.05	0.01	0.1	0.01	0.01	0.01	0.05	0.001	0.01
Omit Midtown, Fin. Dist., hosp.			•						•			
Only main FRBNY building		•	•	•	•	•		•	•	•	•	•
Omit transit hubs	•	•	•	•	•	•	•	•	•	•	•	•
Control for Manhattan activity	•	•	•	•	•	•	•	•	•	•	•	•
Weekday controls	•	•	•	•	•	•	•	•	•	•	•	•
Year-month FE, clustering	•	•	•	•	•	•	•	•	•	•	•	•
Significance-maximising windows	•	•	•	•	•		•	•	•	•	•	
Pseudo-R^2	0.09	0.09	0.08	0.11	0.08	0.09	0.09	0.10	0.08	0.10	0.10	0.11
Observations	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425
Number of candidate models	390	390	390	130	1690	1690	390	390	390	130	1690	1690

Notes: Coincidences are modelled as Poisson processes with intensity given by Eq. 1, and the count of extra rides over the FOMC window is the associated average partial effect times the typical number of weekdays during the window. All coincidental drop-offs are within 1/4 block and 10 minutes of each other. Individual p-values are right-tail quantiles, are obtained from pairs bootstrapping at the year-month level with 100000 simulations and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation. Data-mining-robust significance is obtained using the Romano and Wolf (2005) StepM procedure, and details are provided in Appendix A.4. Counts of candidate windows can vary across specifications due to variation in data sparsity. Regressions span a filtered set of weekdays from 2009 through 2014. Windows beginning from 0:00 through 4:00 are treated as part of the preceding calendar day. All specifications employ vertex shifts of 100 feet outwards. Table A.4 provides additional definitions.
**/* indicates individual significance at the 1%/5% confidence level. † indicates a pre-specified window parameter.

Table 4: Robustness of the increase in lunchtime coincidences to the pre-specification of windows, changes in the vertex shift and variation in model selection

Passenger count:	*Any number*						*Singletons*					
Candidate windows:	*Pre-specified*			*All FOMC × lunchtime*			*Pre-specified*			*All FOMC × lunchtime*		
	i	*ii*	*iii*	*iv*	*v*	*vi*	*vii*	*viii*	*ix*	*x*	*xi*	*xii*
	Windows yielding the most significant increase in coincidental drop-offs											
First event day of FOMC window	$-8^\dagger$	$-1^\dagger$	$-1^\dagger$	-1	-2	-1	$-8^\dagger$	$-1^\dagger$	$-1^\dagger$	-5	-6	-1
Last event day of FOMC window	$+7^\dagger$	$+6^\dagger$	$+1^\dagger$	$+6$	$+7$	$+6$	$+7^\dagger$	$+6^\dagger$	$+1^\dagger$	$+7$	$+7$	$+7$
Start of intraday window	11:00†	11:00†	11:00†	11:00	11:00	11:00	11:00†	11:00†	11:00†	11:00	11:00	11:00
End of intraday window	13:59†	12:59†	12:59†	12:59	12:59	12:59	13:59†	12:59†	12:59†	12:59	12:59	12:59
	Change in coincidental drop-offs during FOMC window											
Partial effect (%)	21.1*	67.3**	63.6**	98.5**	48.2**	67.3**	61.5**	87.9**	84.3**	170.6**	77.5**	108.8**
t-statistic	(2.15)	(4.15)	(3.24)	(3.97)	(4.02)	(4.15)	(3.32)	(3.57)	(3.20)	(4.02)	(4.05)	(4.30)
Extra rides per FOMC window	0.93	0.95	0.51	0.59	1.44	0.95	1.25	0.62	0.35	0.63	1.35	0.85
Individual p-value	0.016	<0.001	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	<0.001	<0.001	<0.001
Data-mining-robust significance	>0.1	0.01	0.05	0.01	0.01	0.01	0.05	0.05	0.05	0.01	0.01	0.001
Vertex shift (feet)	100	100	100	50	150	100	100	100	100	50	150	100
Significance-maximising windows				•	•					•	•	
t-statistic-maximising windows						•						•
Pseudo-R^2	0.08	0.09	0.08	0.07	0.10	0.09	0.10	0.10	0.09	0.11	0.10	0.11
Observations	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425
Number of candidate models	390	390	390	390	390	390	390	390	390	390	390	390

Notes: Coincidences are modelled as Poisson processes with intensity given by Eq. 1, and the count of extra rides over the FOMC window is the associated average partial effect times the typical number of weekdays during the window. The pre-specified windows are *a*. the full lunchtime window over the full set of event days (event days −8 through +7, 11:00-13:59); *b*. the intersection of the windows selected from the lunchtime data mining exercises (event days −1 through +6, 11:00-12:59); and *c*. the subset of the intersection from the first date of an FOMC meeting through the final date of the blackout window (event days −1 through +1, 11:00-12:59). All specifications employ the conservative approach: all coincidental drop-offs are within 1/4 block and 10 minutes of each other; coincidences at transit hubs and the major commercial banks' buildings are omitted, and FRBNY pick-ups only are only in the vicinity of its headquarters. Standard errors are clustered at the year-month level. Individual p-values are right-tail quantiles, are obtained from pairs bootstrapping at the year-month level with 100000 simulations and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation. Data-mining-robust significance is obtained using the Romano and Wolf (2005) StepM procedure, and details are provided in Appendix A.4. In the assessment of data-mining-robust significance where windows are pre-specified, the set of all pairs of FOMC and lunchtime windows is employed. Regressions span a filtered set of weekdays from 2009 through 2014. Windows beginning from 0:00 through 4:00 are treated as part of the preceding calendar day. Table A.4 provides additional definitions.
**/* indicates individual significance at the 1%/5% confidence level. † indicates a pre-specified window parameter.

Table 5: Robustness of the increase in lunchtime coincidences to variation in the choice of covariates, the definition of a coincidental drop-off and geographic filtration

Candidate windows:	*All FOMC × lunchtime*											
Passenger count:	*Any number*						*Singletons*					
	i	*ii*	*iii*	*iv*	*v*	*vi*	*vii*	*viii*	*ix*	*x*	*xi*	*xii*
	Windows yielding the most significant increase in coincidental drop-offs											
First event day of FOMC window	−1	−2	−1	−7	−1	−1	−8	−8	−8	−8	−7	−2
Last event day of FOMC window	+7	+7	+7	+6	+7	+7	+7	+7	+7	+7	+7	+7
Start of intraday window	11:00	11:00	11:00	11:00	11:00	11:00	11:00	11:00	11:00	11:00	11:00	11:00
End of intraday window	13:59	12:59	12:59	12:59	12:59	12:59	12:59	12:59	12:59	13:59	13:59	12:59
	Change in coincidental drop-offs during FOMC window											
Partial effect (%)	47.9**	47.9**	38.5**	76.9**	76.3**	25.8**	96.1**	82.3**	59.2**	116.9**	78.0**	43.9**
t-statistic	(3.81)	(3.59)	(2.76)	(3.72)	(3.69)	(2.42)	(4.24)	(4.29)	(3.63)	(3.99)	(3.72)	(2.94)
Extra rides per FOMC window	1.14	0.97	0.98	0.58	0.78	0.89	1.24	1.14	1.27	0.71	0.89	0.86
Individual p-value	<0.001	<0.001	0.004	<0.001	<0.001	0.009	<0.001	<0.001	<0.001	<0.001	<0.001	0.002
Data-mining-robust significance	0.01	0.05	>0.1	0.05	0.05	>0.1	0.01	0.01	0.05	0.01	0.05	>0.1
Coincidence max. distance (blocks)	1/4	1/4	1/4	1/8	1/8	1/4	1/4	1/4	1/4	1/8	1/8	1/4
Coincidence max. interval (min)	10	10	10	10	20	20	10	10	10	10	20	20
Only main FRBNY building	•	•		•	•	•	•	•		•	•	•
Omit transit hubs	•	•		•	•	•	•	•		•	•	•
Control for Manhattan activity			•	•	•	•			•	•	•	•
Weekday controls	•		•	•	•	•	•		•	•	•	•
Year-month FE, clustering	•		•	•	•	•	•		•	•	•	•
White standard errors		•						•				
Significance-maximising windows	•	•	•	•	•	•	•	•	•	•	•	•
Pseudo-R^2	0.09	0.01	0.08	0.07	0.08	0.08	0.09	0.01	0.08	0.09	0.08	0.08
Observations	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425	1425
Number of candidate models	390	390	390	390	390	390	390	390	390	386	389	390

Notes: Coincidences are modelled as Poisson processes with intensity given by Eq. 1, and the count of extra rides over the FOMC window is the associated average partial effect times the typical number of weekdays during the window. Individual p-values are right-tail quantiles, are obtained from pairs bootstrapping at the year-month level with 100000 simulations and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation. Data-mining-robust significance is obtained using the Romano and Wolf (2005) StepM procedure, and details are provided in Appendix A.4. Counts of candidate windows can vary across specifications due to variation in data sparsity. Regressions span a filtered set of weekdays from 2009 through 2014. Windows beginning from 0:00 through 4:00 are treated as part of the preceding calendar day. All specifications employ vertex shifts of 100 feet outwards. Table A.4 provides additional definitions. **/* indicates individual significance at the 1%/5% confidence level.

A Appendices

A.1 Additional robustness checks

Placebo tests provide additional support for a connexion between monetary-policy meetings and increases in interaction between New York Fed insiders and commercial-bank insiders. I reëstimate the significance-maximising specifications but with the FOMC windows shifted by -4 through $+4$ weeks. With both the baseline and conservative rides from the major commercial banks to the New York Fed, no shift away from the actual meeting week yields a statistically significant increase or an increase of anywhere close to the same order of magnitude (Figure A.3). Figure A.4 Panels A and B show the same for both the conservative and single-passenger conservative lunchtime coincidences with one trivial exception. The exceptional case is for single-passenger conservative coincidences when the offset is $+1$ week. The associated significance-maximising FOMC window spans event days -8 through $+7$, so a large volume of rides in the week after an FOMC meeting would mechanically impact that particular offset. I repeat the placebo tests for lunchtime coincidental drop-offs but with shifts of the span from event day -1 through $+1$. Panels C and D show clear specificity of the increase in coincidences to the span containing the FOMC announcement.

Tables A.6 and A.7 respectively demonstrate the robustness of the increases in direct rides and coincidences to changes in the sample period, the choice of the vicinity of a building and the choice of regression approach. I do not repeat the data-mining exercise but show that the results for the significance-maximising windows are not fragile. When the only dates that I filter out are statutory holidays, Christmas through New Year's Day and dates of major hurricane-related disruption, the changes are minor (Columns *i* and *vii*). When I use buildings' entire blocks as their vicinities, I generally find slightly larger increases in units of rides and smaller changes in percentage terms. The results remain individually highly statistically significant, but the t-statistics are lower (Columns *ii* and *viii*). Together these results suggest that the expansions are mostly adding noise. Columns *iii* and *ix* present a particularly simple and naïve specification: a Poisson regression of rides only on a constant and the event indicator where I *i.*) only remove the holiday periods and hurricanes; *ii.*) use buildings' blocks as their vicinities; *iii.*) use both FRBNY buildings; *iv.*) use White standard errors; and, for, coincidental drop-offs, *v.*) do not filter drop-offs at transit hubs out. Relative to the original regressions, changes in percentage terms are lower, and changes in rides are similar.

The t-statistics are lower, but the changes are individually highly statistically significant.

I obtain similar results when I use a much simpler econometric approach and simply perform OLS regressions, use simple standard errors that account for neither heteroskedasticity nor serial correlation and employ asymptotic p-values. Estimation of the baseline and conservative specifications for direct rides and the conservative and single-passenger-conservative specifications for coincidental drop-offs yields similar changes to those from the Poisson regressions both in units of rides and in percentage terms (Columns *iv* and *x*). The t-statistics are comparable, and the individual p-values are all below 0.001.[19] When I run the regressions only on a constant and the indicator for the FOMC window, the percentage changes, changes in units of rides and t-statistics generally fall at least somewhat, but they remain comparable (Columns *v* and *xi*). The individual p-values remain below 0.001. Finally, I repeat the simple, naïve approach of Columns *iii* and *ix* but with the basic OLS estimation. The percentage changes and changes in units are essentially identical to those with Poisson estimation, and the p-values remain below 0.001. (Columns *vi* and *xii*).

A.2 Vicinity of the New York Fed

The New York Fed's headquarters is located at 33 Liberty Street, and FRBNY staff are also located across the street to the East at 33 Maiden Lane (Federal Reserve Bank of New York, n.d.(a)). A few hundred FRBNY staff are located at a third Manhattan office at Three World Financial Center, but high-level New York Fed correspondence indicates that none of the staff working in credit markets or banking supervision could be based there (Cumming 2010 and Frierson 2010).[20] Insofar as only variation in rides driven by monetary-policy and regulatory events are relevant to this paper, I only consider rides to and from 33 Liberty Street and 33 Maiden Lane. Annual reports from 2009 through 2014 indicate no fewer than 2972 FRBNY officers and employees, so even with allowances for embedded staff, Three World Financial Center and operations in New Jersey, it is reasonable that an important share of the taxi traffic to and from the vicinities of 33 Liberty Street and 33 Maiden Lane locations reflects New York Fed business and the activities of its staff.

[19] The percentage change for the OLS regressions is calculated as the percentage difference between the average fit rides over days in the FOMC windows when the window indicator is on and the average fit rides over days in the FOMC windows when the window indicator is off.

[20] "We also understand ... that the Bank will not permit supervision or credit market staff to occupy Three World Financial Center. The Bank intends to relocate its automation staff to the new space." (Frierson 2010)

33 Liberty Street occupies its entire block, so all rides mapped to that block are mapped to the New York Fed. 33 Maiden Lane only occupies the northern part of its block, and only rides mapped to the area of that building are mapped to the New York Fed. Given that 33 Liberty Street is the New York Fed's main building, and 33 Maiden Lane's main entrance is across from 33 Liberty Street, conservative specifications only employ rides mapped to an expansion of 33 Liberty Street's block.

As these buildings are in the Financial District, they are not isolated from other financial and legal institutions. JPMorgan Chase has a back office across the street to the West (One Chase Manhattan Plaza), and the boutique investment bank Brown Brothers Harriman is located within a block (140 Broadway). The headquarters of the law firm Milbank, Tweed, Hadley & McCloy is also located at One Chase Manhattan Plaza. A condominium which shares a corner with 33 Liberty Street (10 Liberty Street) and a hotel across from 33 Liberty Street (51 Nassau Street) could also be important sources and destinations of rides, particularly in the morning and at night. Assorted restaurants, shops and private residences are also located in the immediate vicinity. While these adjacent buildings would be expected to drive a share of the rides mapped to the blocks of the New York Fed, their presence is not necessarily a serious threat to the identification of variation in New York Fed insiders' interactions around FOMC meetings. Rides to and from the unrelated locations would have to vary systematically around monetary-policy meetings for them to pose more of a problem than just the addition of noise.

A.3 Estimation details

The potential for sparse rides necessitates a filtering of coefficients. In the calculation of standard errors, I cluster at the year-month level. The effective number of clusters is equal to the number of months with non-zero observations, so I omit particularly sparse windows to avoid unreliable standard errors. Specifically, for a given ride type and FOMC window, I drop any intraday windows for which there are positive rides in fewer than 36 of the 72 months. In general, an absence of observations during an FOMC window theoretically yields a coefficient estimate of $-\infty$ and an undefined standard error. As the numerical estimation may return a highly negative but finite value instead, I drop coefficients corresponding to a decrease by a factor of at least 0.9999. As a guard against unrealistic estimates from sparse data, I also perform the mirror-image filtration and drop any coefficients corresponding to an increase by a factor of at least 10000. As a precaution against unreliable estimates due to near-singularity, I omit any coefficients for which the matrix to be inverted in the calculation of a standard error has a return condition of less than or equal to 1×10^6.

I employ asymptotic refinement in the calculation of bootstrapped p-values. Each simulation is a draw of 72 year-month observations with replacement. I follow Cameron, Gelbach and Miller (2008) and Cameron and Trivedi (2009) in employing the empirical distribution of the standardised deviations from the coefficient obtained from the unsimulated data. Non-positivity of a coefficient is rejected at the $1-\alpha$ confidence level when its t-statistic exceeds the α quantile of the empirical distribution.

To reduce the computational burden, the number of bootstrap simulations employed in the production of Figures 4, 5, 7, A.3 and A.4 is a function of the significance level of interest. My interest there is only in whether changes are significant at at least the 5% confidence level, and I initially obtain bootstrapped p-values for all coefficients with t-statistics greater than 1.25 using 10000 simulations. When I observe a p-value of 0.005 or below, I subsequently employ 100000 simulations to assess significance at the 0.1% confidence level.

A.4 Data-mining-robust significance

To assess the significance of increases conditional on data mining, I follow the StepM procedure with studentisation described in Romano and Wolf (2005) and Romano, Shaikh and Wolf (2008). This is a step-down procedure that seeks to maximise the number of rejected null hypotheses for a given type-I error rate α. To fix concepts, let $\{\beta_i\}, i \in \{1, 2, ..., N\}$ be a set of true parameters, and let $\{\hat{\beta}_i\}$ and $\{\hat{\sigma}_i\}$ be respectively their point estimates and standard errors. I seek to answer which $\beta_j \in \{\beta_i\}$ are significantly greater than 0.

The Romano and Wolf (2005) StepM procedure is based on the order statistics of simulated estimates' deviations from those obtained from the original data. When one employs studentisation, one first simulates M realisations of the N estimates' standardised deviations from the true values. For each of the M simulations, one obtains the maximum standardised deviation. Let q_1^α denote the $1-\alpha$ quantile of that distribution. One rejects the null hypothesis of non-positivity for any β_i

for which $\hat{\beta}_i/\hat{\sigma}_i$ is greater than q_1^α. Using the same simulations, one proceeds to calculate the $1-\alpha$ quantile of the distribution of maxima for the random variables for which the null was not rejected, henceforth q_2^α. One then rejects the null for any β_i for which $\hat{\beta}_i/\hat{\sigma}_i$ is greater than q_2^α. This process continues until no additional null hypotheses are rejected.

This assessment of significance is conservative in that it asymptotically provides an upper bound (Romano and Wolf 2005). This approach does, however, provide power benefits over a simple Bonferroni correction in that the Bonferroni assumption that estimates are independent imposes the highest bar for a finding of significance (Romano and Wolf 2005).[21] The overlap of the intraday windows guarantees at least some dependence. Additional dependence will be introduced if the decision to meet during a certain window is a function of the timing of proximate interactions.

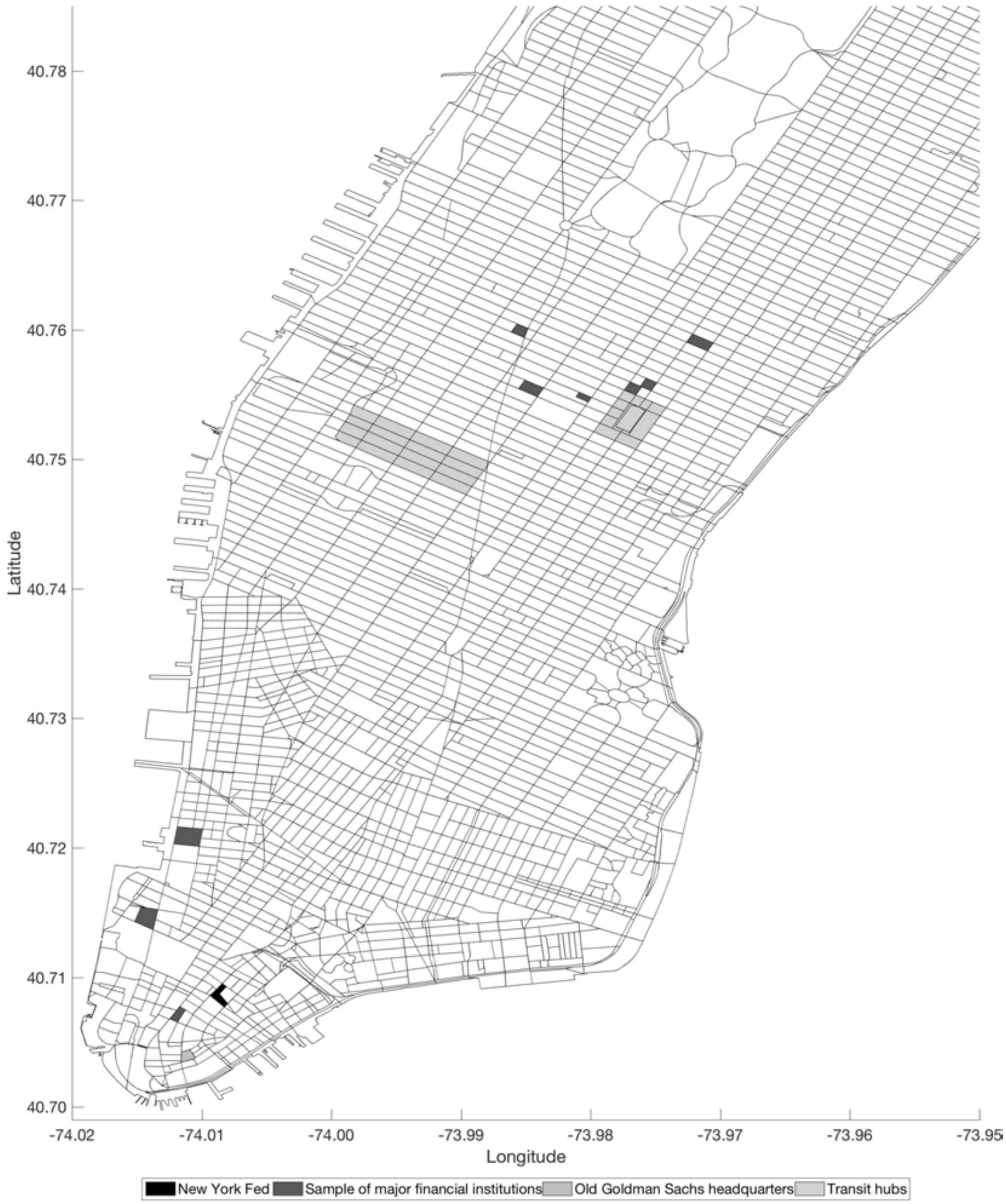
Romano and Wolf (2005) present a bootstrap-based approach applicable to a wide variety of random variables, but bootstrapping here is problematic. Given that I require information about the tail of the maximum over hundreds of coefficients, I require an extremely large number of simulations. Obtaining a sufficient number of bootstrap simulations for such a large number of coefficients for which there is not an analytic solution is not feasible. Moreover, the block bootstrapping at the year-month level oversamples outliers in what are already leptokurtic data: magnitudes with a probability of less than 1 in 1425 may be drawn with probability 1 in 72. With hundreds of coefficients per simulation, there is a danger that the maxima for a non-trivial number of bootstrap simulations could be driven by the oversampling of outliers.

Instead of bootstrapping, I exploit the properties of GMM estimates and employ Monte Carlo simulation. For the GMM estimation, I collect all of the models' Poisson-regression moment conditions. The point estimates are the same as when the regressions are performed individually. In the estimation of the covariance matrix, I impose no restrictions on the covariances of errors for the days in month i both within and across models, and I impose that all errors in month i be independent of all errors in month j for $i \neq j$. The covariance matrices for the individual regressions are along the diagonal. Asymptotically, joint draws of standardised deviations from

[21] A Bonferroni correction is the division of the individual-coefficient p-value by the number of estimates examined.

the true coefficients are distributed normally with mean 0 and with a covariance matrix equal to the coefficients' correlation matrix. To obtain a reasonably good picture of the right tail of the distribution of maxima, I take 1000000 draws from a multivariate normal distribution with mean 0 and a covariance matrix equal to the estimated correlation matrix. Each step of the StepM procedure uses the same set of simulations and simply removes from the calculation of the maxima the contributions of the models for which non-positivity has been rejected.

Figure A.1: Locations of the New York Fed, major commercial banks and the vicinities of transit hubs

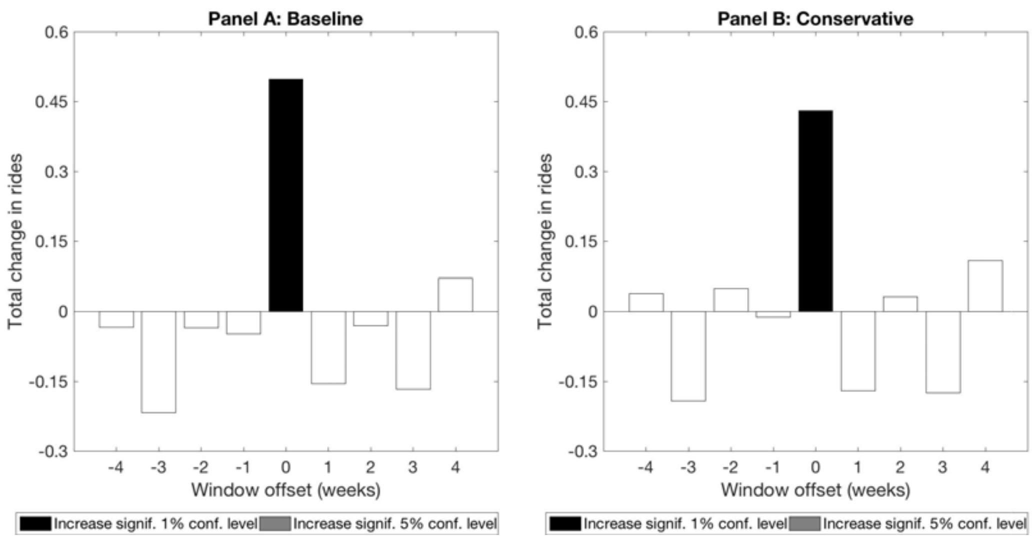


Notes: The New York Fed's locations are 33 Liberty Street and 33 Maiden Lane. The commercial banks' locations are the Manhattan headquarters of American G-SIBs' corporate, investment banking, global markets or investment management headquarters during the period spanning 2009 through 2014. The areas include the boundaries of the physical buildings as well as adjacent sidewalks, roads and plazas. Goldman Sachs moved from its old headquarters in late 2009, and the old headquarters is only used in a data validation exercise.

Figure A.2: Locations of lunchtime coincidental drop-offs around an FOMC announcement

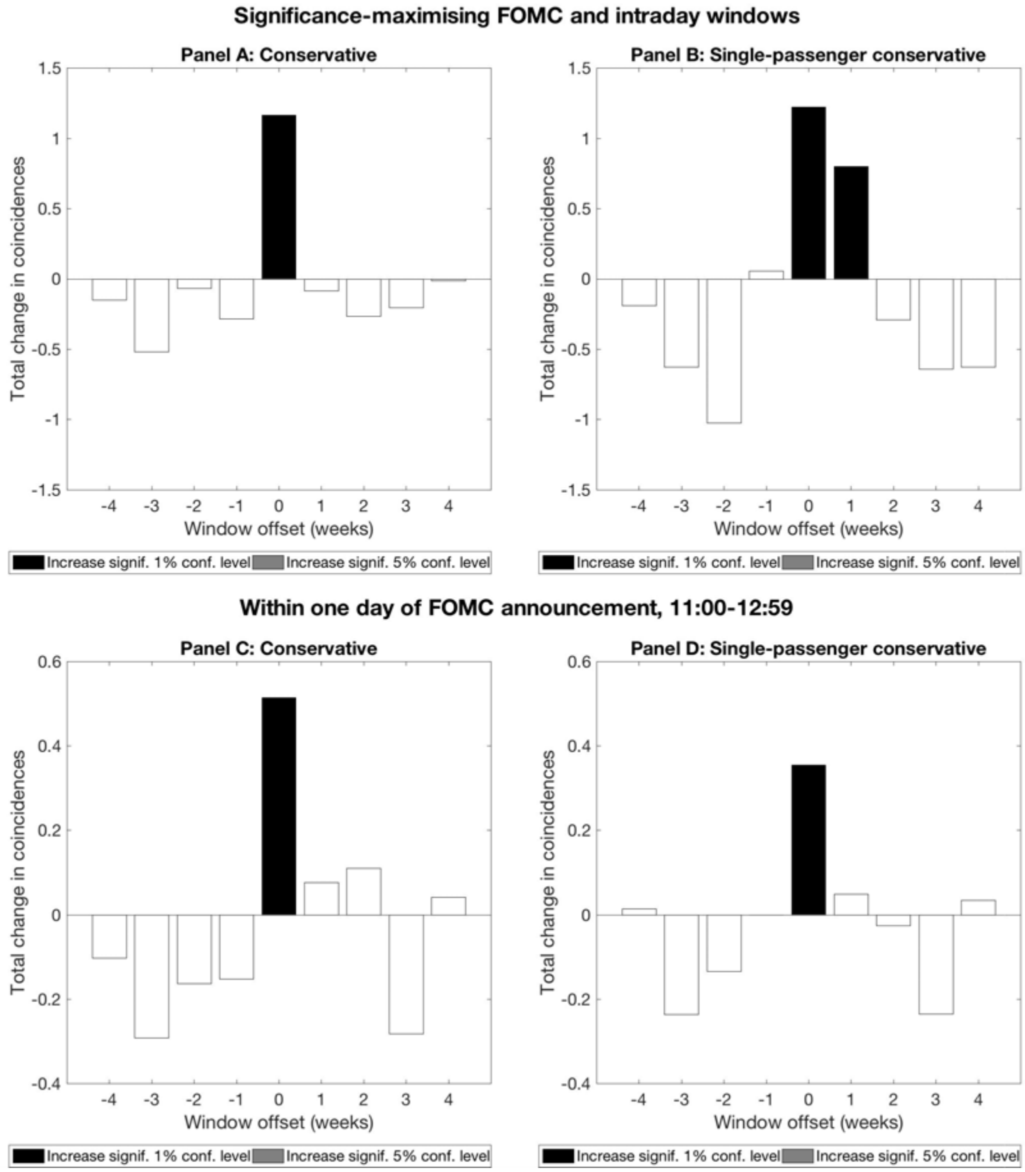
Notes: The lunchtime period spans 11:00 through 13:59. The period around an FOMC announcement spans the weekdays from a week before the typical start of an FOMC meeting, eight days before the announcement, through a week after the announcement. Pick-ups are from 33 Liberty Street or 33 Maiden Lane and from significant front-office presences of major commercial banks. To be classified as a coincidence, drop-offs must *i.*) be mapped to the same block; *ii.*) be within a quarter of a block (66 feet) of each other along the NS and EW axes; and *iii.*) occur within ten minutes of each other. The plotted drop-offs are those of rides originating in the vicinity of the New York Fed. 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.

Figure A.3: Placebo tests for the peculiarity of elevated post-blackout rides to the weeks of FOMC meetings



Notes: Rides are from significant front-office presences of major commercial banks to the New York Fed between 1:00 and 4:00 after the midnight end of the FOMC blackout. The baseline specification includes rides both to the vicinities of 33 Liberty Street and 33 Maiden Lane. The conservative specification only includes rides to the vicinity of the FRBNY headquarters at 33 Liberty Street, an area that includes the main entrance to 33 Maiden Lane. Poisson regressions on event indicators, year-month fixed effects, weekday indicators and aggregate Manhattan ride volume are repeated with shifts of the meeting indicators by four weeks backward through four weeks forward. Increases that are significant at the 1% or 5% confidence level are shaded. One-sided p-values for coefficients with t-statistics greater than 1.25 are obtained from pairs bootstrapping of year-month observations with 10000 repetitions and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation.

Figure A.4: Placebo tests for the peculiarity of elevated lunchtime coincidences to spans containing FOMC meetings



Notes: Pick-ups occur around the New York Fed's headquarters at 33 Liberty Street and locations where major commercial banks have significant front-office presences in Manhattan. For both the conservative and the single-passenger conservative specifications of coincidences, regressions on event indicators, year-month fixed effects, weekday fixed effects and aggregate Manhattan ride volume are repeated with shifts of the meeting indicators by four weeks backward through four weeks forward. The significance-maximising windows for the conservative specification are from the day before the shifted meeting until the seventh day afterwards and from 11:00 to 13:59. Those for the single-passenger-conservative specification are the eighth day before the shifted meeting until the seventh thereafter and 11:00-12:59. The single-passenger conservative specifications requires a single passenger in each taxi. Increases that are significant at the 1% or 5% confidence level are shaded. One-sided p-values for coefficients with t-statistics greater than 1.25 are obtained from pairs bootstrapping of year-month observations with 10000 repetitions and employ asymptotic refinement. Appendix A.3 provides additional details on the estimation.

Table A.1: List of buildings occupied by the Federal Reserve Bank of New York and major commercial buildings that are employed in this paper.

Institution	*Address*
Federal Reserve Bank of New York (headquarters)	33 Liberty Street
Federal Reserve Bank of New York	33 Maiden Lane
Bank of America (investment banking)	One Bryant Park
BNY Mellon (headquarters)	One Wall Street
Citigroup (headquarters during sample)	399 Park Avenue
Citigroup (global markets)	388-390 Greenwich Street
Goldman Sachs (headquarters)	200 West Street
Goldman Sachs (old headquarters)	85 Broad Street
JPMorgan Chase (headquarters)	270 Park Avenue
JPMorgan Chase (investment banking)	383 Madison Avenue
Morgan Stanley (headquarters)	1585 Broadway
Morgan Stanley (investment management)	522 5th Avenue

Notes: The commercial banks are American G-SIBs with significant front-office presences in Manhattan during the sample period of 2009 through 2014. A significant front-office presence is defined as corporate headquarters or the headquarters of the banks' investment banking, global markets or investment management divisions. Goldman Sachs completed its move to a new headquarters in 2010, and its old headquarters is only used in a data-validation exercise.

Table A.2: Example timeline of *i.*) Federal Reserve monetary policy events and *ii.*) Cieślak, Morse and Vissing-Jørgensen (2016) week 0

		Event day	*Federal Reserve event*	*Week 0 (Cieślak, Morse and Vissing-Jørgensen 2016)*
Week a	Monday	-9		
	Tuesday	-8	Communications blackout begins	
	Wednesday	-7		
	Thursday	-6		
	Friday	-5		
Week b	Monday	-2	Discount rate meeting	
	Tuesday	-1	FOMC meeting begins	Week 0 begins
	Wednesday	0	FOMC announcement	
	Thursday	$+1$	Communications blackout ends	
	Friday	$+2$		
Week c	Monday	$+5$		Week 0 ends
	Tuesday	$+6$		
	Wednesday	$+7$		
	Thursday	$+8$		
	Friday	$+9$		

Notes: Spans include the full calendar days marked as their end points. The span of the communications blackout period reflects Federal Reserve policy during the sample period of 2009-2014.

Table A.3: Counts and shares of event days during the sample period

	Day count	*Sample share (%)*
All days	1425	100
Event day -8	46	3.2
Event day -7	47	3.3
Event day -6	47	3.3
Event day -5	46	3.2
Event day -4	8	0.6
Event day -3	1	0.1
Event day -2	39	2.7
Event day -1	48	3.4
Event day 0	48	3.4
Event day $+1$	47	3.3
Event day $+2$	46	3.2
Event day $+3$	8	0.6
Event day $+4$	1	0.1
Event day $+5$	38	2.7
Event day $+6$	45	3.2
Event day $+7$	42	2.9
Event day -8 through $+7$	557	39.1
Event day -1 through $+6$	281	19.7
Event day -1 through $+1$	143	10.0

Notes: A date is mapped to event day X if it is offset from the nearest FOMC announcement date by X calendar days. Negative values indicate dates prior to an FOMC announcement, and positive values indicate dates following an FOMC announcement. The sample is the filtered set of weekdays from the beginning of 2009 through the end of 2014.

Table A.4: Glossary of terms for regression tables

All FOMC windows	Set of all contiguous spans of weekdays from a week before the start of a meeting through a week after its end
Average partial effect	Conversion of a coefficient from a Poisson regression to a representative change in rides. The average partial effect is calculated as the average over the event days for which the change is calculated of the difference between the fit value with the FOMC window indicator on and the fit value with the FOMC window indicator off.
Baseline specification	Pick-up or drop-off at either 33 Liberty Street or 33 Maiden Lane. Coincidental drop-offs cannot occur within a block of Penn Station or Grand Central Terminal.
Block (as distance)	Typical North-South width of Manhattan block (264 feet)
Coincidental drop-off	Passengers picked up near FRBNY and major commercial banks' buildings dropped off at roughly same place and time. The drop-offs must *i.*) be mapped to the same block; *ii.*) be within a specified distance of each other along the NS and EW axes; *iii.*) occur within a specified interval of each other; and *iv.*) not be mapped to the FRBNY or any of the commercial banks.
Conservative specification	Pick-up or drop-off at 33 Liberty Street. Coincidental drop-offs cannot be mapped to Penn Station or Grand Central Terminal or to any of the neighbouring blocks.
Data-mining-robust significance	Highest level of significance in the set $\{0.001, 0.01, 0.05, 0.1, > 0.1\}$ at which the Romano and Wolf (2005) StepM procedure with studentisation rejects the null hypothesis that the coefficient is non-positive. Details are provided in Appendix A.4.
Event day	Offset from the date of the nearest FOMC announcement.
FOMC blackout	Period from the seventh day before the start of an FOMC meeting up to midnight the date after the FOMC announcement during which Federal Reserve regulations tightly restrict staff members' external communication
FOMC window	Span of offsets from the date of an FOMC announcement
Intraday window	Two- or three-hour span beginning at the top of an hour.
Lunchtime windows	11:00-12:59, 12:00-13:59 and 11:00-13:59
Main FRBNY building	33 Liberty Street
Manhattan activity	Average of all pick-ups and drop-offs of within-Manhattan rides over the intraday window
Partial effect	Percentage change in rides during an FOMC window. The partial effect of a meeting window indicator with coefficient β_ι is $(exp(\beta_\iota) - 1) \times 100\%$.
Pseudo-R^2	$1 - \frac{\text{sum of squared residuals}}{\text{total sum of squares}}$
Significance-maximising windows	Windows that maximise the average of the change in rides by its quantile by t-statistic and its quantile by additional rides.
t-statistic-maximising windows	Windows that maximise the t-statistic of the change in rides.
Transit hub	Grand Central Terminal or Penn Station
Major commercial bank	American Global Systemically Important Bank with its corporate, investment-banking, investment-management or financial-markets division headquartered in Manhattan. This paper only employs those headquarters.
Vertex shift	Distance by which each vertex of a block or an institutional area is moved out from its centroid to capture rides on the opposite sides of streets and to reduce the rides lost to GPS noise
Working-day windows	Set of all two- and three-hour windows beginning at the start of an hour within the span 9:00 through 16:59. 9:00 through 16:59 is a span during which one might expect taxis to be largely occupied by individuals travelling for work purposes or on a break from work.

Table A.5: Coincidental lunchtime drop-offs with potential return trips to the New York Fed

Passenger count:	*Any number*		*Singletons*	
	i	*ii*	*iii*	*iv*
	Significance-maximising windows			
First event day of FOMC window	−1	−2	−8	−8
Last event day of FOMC window	7	6	7	7
Start of intraday window	11:00	11:00	11:00	11:00
End of intraday window	13:59	12:59	12:59	12:59
Coincidental drop-offs	164	70	120	65
Potential return trips	29	13	19	12
Share of coincidental drop-offs matched (%)	17.7	18.6	15.8	18.5
Omit Midtown, Fin. Dist., hosp.		•		•

Notes: This table presents counts of lunchtime coincidental drop-offs during the significance-maximising windows and the number of those rides for which a potential return trip to the New York Fed is identified. A highly liberal criterion for the matching is employed: the pick-up for the return trip must occur *i*.) at least 5 minutes after the later of the two coincidental drop-offs; *ii*.) no more than 90 minutes after the later of the two coincidental drop-offs; and *iii*.) no more than 1000 feet along the NS or EW axes from the drop-off for the passenger picked up near the New York Fed. In the case of coincidences of single-passenger drop-offs, the return trip must also have a single passenger. All columns employ the conservative specification with vertex shifts of 100 feet and maximum separations for coincidences of 1/4 block and 10 minutes. Table A.4 provides additional definitions.

Table A.6: Robustness of the increase in late-night post-FOMC-blackout rides from major commercial banks to the New York Fed to variation in data cleaning, the use of the full blocks of buildings and the selection of estimation method

Ride count:	*Baseline*						*Conservative*					
Estimation method:	*Poisson*			*OLS*			*Poisson*			*OLS*		
	i	*ii*	*iii*	*iv*	*v*	*vi*	*vii*	*viii*	*ix*	*x*	*xi*	*xii*
	Windows previously found to yield the most significant increase in rides											
First event day of FOMC window	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†
Last event day of FOMC window	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†	+1†
Start of intraday window	1:00†	1:00†	1:00†	1:00†	1:00†	1:00†	1:00†	1:00†	1:00†	1:00†	1:00†	1:00†
End of intraday window	3:59†	3:59†	3:59†	3:59†	3:59†	3:59†	3:59†	3:59†	3:59†	3:59†	3:59†	3:59†
	Change in rides from major commercial banks to FRBNY during FOMC window											
Partial effect (%)	107.7**	67.8**	61.2**	106.5**	76.6**	61.2**	122.0**	106.7**	95.8**	117.2**	98.0**	95.8**
t-statistic	(4.70)	(3.87)	(3.62)	(4.34)	(3.58)	(3.95)	(4.45)	(4.24)	(3.73)	(4.35)	(3.95)	(4.24)
Extra rides per FOMC window	0.49	0.70	0.65	0.49	0.42	0.65	0.42	0.48	0.45	0.42	0.39	0.45
Individual p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Only remove holidays, hurricanes	•		•			•	•		•			•
Use full block as building vicinity		•	•			•		•	•			•
Control for Manhattan activity	•	•		•			•	•		•		
Weekday controls	•	•		•			•	•		•		
Year-month FE	•	•		•			•	•		•		
Year-month clustering	•	•					•	•				
White standard errors			•						•			
Simple OLS standard errors				•	•	•				•	•	•
Pseudo-R^2	0.21	0.20	0.01	0.19	0.01	0.01	0.18	0.18	0.01	0.17	0.01	0.01
Observations	1475	1425	1475	1425	1425	1475	1475	1425	1475	1425	1425	1475

Notes: For the Poisson regressions, rides are modelled as Poisson processes with intensity given by Eq. 1, and the count of extra rides over the FOMC window is the associated average partial effect times the typical number of weekdays during the window. For the OLS regressions, the expected value of rides is the term in the exponent in Eq. 1, and the partial effect is percentage by which the average level of rides during dates that fall in the FOMC window is greater than the average of their fit level when the FOMC window indicator is off. Baseline rides have drop-offs in the vicinity of either 33 Liberty Street or 33 Maiden Lane. Conservative rides have drop-offs only in the vicinity of the FRBNY headquarters at 33 Liberty Street, an area that includes the main entrance to 33 Maiden Lane. Individual p-values for the Poisson regressions are right-tail quantiles, are obtained from pairs bootstrapping at the year-month level with 100000 simulations and employ asymptotic refinement. All p-values for OLS regressions are asymptotic right-tail quantiles based on simple OLS standard errors. Regressions span filtered sets of weekdays from 2009 through 2014. Windows beginning from 0:00 through 4:00 are treated as part of the preceding calendar day. All specifications employ vertex shifts of 100 feet outwards. Table A.4 provides additional definitions.
**/* indicates individual significance at the 1%/5% confidence level. † indicates a pre-specified window parameter.

Table A.7: Robustness of the increase in lunchtime coincidences to variation in data cleaning, the use of the full blocks of buildings and the selection of estimation method

Passenger count:	*Any number*						*Singletons*					
Estimation method:	*Poisson*			*OLS*			*Poisson*			*OLS*		
	i	*ii*	*iii*	*iv*	*v*	*vi*	*vii*	*viii*	*ix*	*x*	*xi*	*xii*
	Windows previously found to yield the most significant increase in coincidental drop-offs											
First event day of FOMC window	$-1^\dagger$	$-1^\dagger$	$-1^\dagger$	$-1^\dagger$	$-1^\dagger$	$-1^\dagger$	$-8^\dagger$	$-8^\dagger$	$-8^\dagger$	$-8^\dagger$	$-8^\dagger$	$-8^\dagger$
Last event day of FOMC window	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$	$+7^\dagger$
Start of intraday window	11:00†	11:00†	11:00†	11:00†	11:00†	11:00†	11:00†	11:00†	11:00†	11:00†	11:00†	11:00†
End of intraday window	13:59†	13:59†	13:59†	13:59†	13:59†	13:59†	12:59†	12:59†	12:59†	12:59†	12:59†	12:59†
	Change in coincidental drop-offs during FOMC window											
Partial effect (%)	45.5**	36.9**	26.5**	48.3**	38.2**	26.5**	92.6**	72.1**	52.2**	100.0**	82.3**	52.2**
t-statistic	(3.47)	(3.33)	(3.08)	(3.83)	(3.39)	(3.14)	(4.06)	(3.73)	(3.94)	(4.39)	(4.36)	(3.96)
Extra rides per FOMC window	1.07	1.15	1.11	1.14	0.97	1.11	1.18	1.32	1.26	1.26	1.14	1.26
Individual p-value	<0.001	<0.001	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Only remove holidays, hurricanes	•		•			•	•		•			•
Use full block as building vicinity		•	•			•		•	•			•
Only main FRBNY building	•	•		•	•		•	•		•	•	
Omit transit hubs	•	•		•	•		•	•		•	•	
Control for Manhattan activity	•	•		•			•	•		•		
Weekday controls	•	•		•			•	•		•		
Year-month FE	•	•		•			•	•		•		
Year-month clustering	•	•					•	•				
White standard errors			•						•			
Simple OLS standard errors				•	•	•				•	•	•
Pseudo-R^2	0.09	0.09	0.01	0.09	0.01	0.01	0.10	0.09	0.01	0.09	0.01	0.01
Observations	1475	1425	1475	1425	1425	1475	1475	1425	1475	1425	1425	1475

Notes: For the Poisson regressions, coincidences are modelled as Poisson processes with intensity given by Eq. 1, and the count of extra rides over the FOMC window is the associated average partial effect times the typical number of weekdays during the window. For the OLS regressions, the expected value of rides is the term in the exponent in Eq. 1, and the partial effect is percentage by which the average level of rides during dates that fall in the FOMC window is greater than the average of their fit level when the FOMC window indicator is off. The significance-maximising windows for the conservative specification are employed when there is no filtration by passenger count, and those for the single-passenger conservative specification are employed when only singletons are considered. The maximum spatial and temporal separations for coincidental drop-offs are 1/4 block and 10 minutes. Individual p-values for the Poisson regressions are right-tail quantiles, are obtained from pairs bootstrapping at the year-month level with 100000 simulations and employ asymptotic refinement. All p-values for OLS regressions are asymptotic right-tail quantiles based on simple OLS standard errors. Regressions span filtered sets of weekdays from 2009 through 2014. Windows beginning from 0:00 through 4:00 are treated as part of the preceding calendar day. All specifications employ vertex shifts of 100 feet outwards. Table A.4 provides additional definitions.
**/* indicates individual significance at the 1%/5% confidence level. † indicates a pre-specified window parameter.

B Data Appendix

B.1 New York City yellow taxi data

The New York City Taxi & Limousine Commission provides public access to its yellow-taxi origin, destination and payment data from 2009 onward at http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml. The Commission reports that it collected the data as part of the Taxicab & Livery Passenger Enhancement Programs, and authorised third-party vendors monitored the taxis on the Commission's behalf. While the Commission does not certify the absence of omissions or errors in the data it received, the data website does state that the Commission "performs routine reviews of the records and takes enforcement actions when necessary to ensure, to the extent possible, complete and accurate information." It is not clear whether data published on the website are ever revised.

These data include GPS coordinates of pick-ups and drop-offs, times of pick-ups and drop-offs, trip distance, trip duration, fares, tips, passenger numbers and the name of the firm that provided each record to the Commission. The medallion number of the cab cannot be assessed from the public files. While the time field is precise to the second, data from a vendor that provided roughly half of the observations appeared to be resolved only to the minute. GPS coordinates are precise to six decimals places. Inspection of where coordinates are relative to roads suggests accuracy of $O(10ft)$ to $O(100ft)$. As examples, Figure B.1 presents all of the recorded pick-up and drop-off locations from 2009-2014 in the vicinity of the Federal Reserve Bank of New York's main offices with block outlines superimposed. Figure B.2 presents the distribution of pick-ups and drop-offs around JPMorgan Chase's headquarters in skyscraper-laden Midtown.

On the data website, the Commission indicates that it provides the data as they were received, and I filter rides out that appear to be duplicates or do not satisfy fairly weak reasonableness conditions:[22]

1. The trip does not have an identical pick-up time and pick-up latitude to those of an already processed ride[23]
2. There is at least one passenger

[22] I omit conditions that are superfluous given the requirement that rides start and end in Manhattan.

[23] This is overly conservative and leads to the dropping of a very small fraction of unique rides. Such infrequent and idiosyncratic omissions would if anything introduce a downward bias in estimated changes in interactions.

3. There are no more than five passengers[24]
4. The total payment is positive
5. The total payment is less than $1000
6. The reported trip distance is at least 0.1 miles[25]
7. The reported trip distance is less than 25 miles[26]
8. The distance from the pick-up location to the drop-off location implied by the GPS coordinates is at least 0.1 miles
9. The difference between the pick-up and drop-off times is greater than twenty seconds
10. The difference between the pick-up and drop-off times is less than two hours

I give each ride a unique identification numbers and keep only rides for which both the pick-up and drop-off are mapped to at least one Manhattan census block. The mapping of rides to census blocks is discussed below. Since each pick-up and drop-off may be mapped to multiple blocks, all ride counts in this paper are counts of unique identification numbers.

B.2 Census blocks and Neighborhood Tabulation Areas

For the mapping of rides to census blocks, I employed the ESRI shapefile for 2010 Census Blocks (Clipped to Shoreline) available at http://www1.nyc.gov/site/planning/data-maps/open-data/districts-download-metadata.page. At the initiation of this work, the available file was 'nycb2010_16b.zip', and I have continued to employ those data. Given that 2010 census blocks are historical data, any changes in their encoding would be expected to have at most a trivial impact on replicability.

To facilitate mapping, I remove all census blocks that contained holes or where at any point the boundary and the interior coincided, *e.g.* a census block shaped like an 8 would satisfy both conditions. Only a very small fraction of rides that start and end in Manhattan will be neglected due to this removal.

Given GPS inaccuracy and the fact that not all pick-ups and drop-offs will occur at the census blocks of the ultimate sources and destinations, I map a coordinate to a census block if the co-

[24]The Commission indicates that a maximum of five adult passengers are permitted (http://www.nyc.gov/html/tlc/downloads/pdf/rule_book_current_chapter_54.pdf).

[25]My prior is that rides of a block or two are less likely to reflect an *ex ante* intention than they are a realisation of a forgotten item or an accidentally started taximeter.

[26]25 miles is excessive when only Manhattan is of interest, but I include it since some rides may be filtered out only as a result of this condition.

ordinate falls in a neighbourhood of that census block. More precisely, I modify the set of filtered census blocks by moving each vertex 100 feet outward from the block's centroid. Consequently, a ride may be mapped to multiple census blocks. Mapping to unmodified census blocks could hardly be considered a more conservative approach since doing so would even neglect drop-offs on the opposite side of the street from a building of interest.

A quirk in the categorisation of census blocks is that not all Manhattan census blocks are on Manhattan Island proper. Liberty Island and a number of Brooklyn docks, for instance, are designated as part of Manhattan. Since this paper focuses on Manhattan Island for geographical reasons, I drop from the list of Manhattan blocks those that are not on the island. To do so, I create a polygon that covers only Manhattan Island and some of the surrounding water, and I only employ blocks that are both categorised as belonging to Manhattan and located completely within that polygon.

Neighborhood Tabulation Areas are obtained by merging 2010 census tracts according to the mapping at https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-nynta.page. The Census Tracts 2010 (Clipped to Shoreline) shapefile data were obtained as nyct2010_17b.zip at https://www1.nyc.gov/site/planning/data-maps/open-data/districts-download-metadata.page.

B.3 FOMC meeting dates

The meeting dates employed in this paper are regularly scheduled FOMC meetings. These dates are available on various pages at https://www.federalreserve.gov/monetarypolicy.

B.4 Filtration of dates

I omit dates on which ride counts are unlikely to reflect FRBNY and G-SIB staff behaviour or may be unreliable. These dates fall into six categories: weekends, statutory holidays, dates around statutory holidays, vendor discrepancies, hurricanes and hurricane-level disruptions. The first step in the filtration is the omission of weekends and the list of federal holidays provided by https://archive.opm.gov/operating_status_schedules/fedhol/2009.asp and the analogous pages for later years.[27] The expectation that non-holiday weekday rides will be dominated by individuals conducting business aids the identification of rides with staff movements and the estimated parameters with insiders' behaviour. While meetings of interest might occur at a weekend or on a holiday, this paper can only capture those for which both the FRBNY and the G-SIB parties are at their workplaces around the meeting time. Inclusion of weekends and holidays would likely add significant noise in the form of unrelated parties' leisure activities but little signal.

There is a significant reduction in overall ride volume not only on the statutory holidays but on many dates adjacent to them. Given this suggestion of deviation from typical business activity and the consistency with priors regarding vacation periods, I omit Christmas Eve through the weekday after the New Year's Day statutory holiday; the weekday after Independence Day; and the weekday after Thanksgiving.

I proceed to filter weekdays on the basis of variation in drop-off counts. In the first place, I seek discrepancies across the vendors that report the data. CMT and VTS each provide about half of the ride data, and DDS provided less than ten per cent until its departure in mid-2010. While the CMT and VTS shares are overall very stable, there are dates on which large volumes of rides appear to be missing for each of them. I proceed to filter any date out for which any vendor's share is at least ten percentage points less than its four-week (twenty-weekday) moving median, a total of twenty-three weekdays.[28,29] The cutoff of ten percentage points is motivated by the trade-off between a desire to minimise data omissions on sample days and a desire to minimise data omissions from the loss of sample days.

Adverse weather can disrupt both taxi and business activity. I consequently filter extreme cases out, starting with Hurricane Irene and Hurricane Sandy. I begin with the sample of weekdays after holiday periods and vendor discrepancies have been removed. I then calculate deviations from twenty-weekday medians.[30] The periods around the hurricanes that I drop are those for which the deviations are visually deemed to be outliers: 29 August 2011 for Hurricane Irene and 29 October 2012 through 2 November 2012 for Hurricane Sandy. Thereafter, I drop all of the filtered

[27] New Year's Day, the Birthday of Martin Luther King, Jr., Washington's Birthday, Memorial Day, Independence Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving Day and Christmas Day

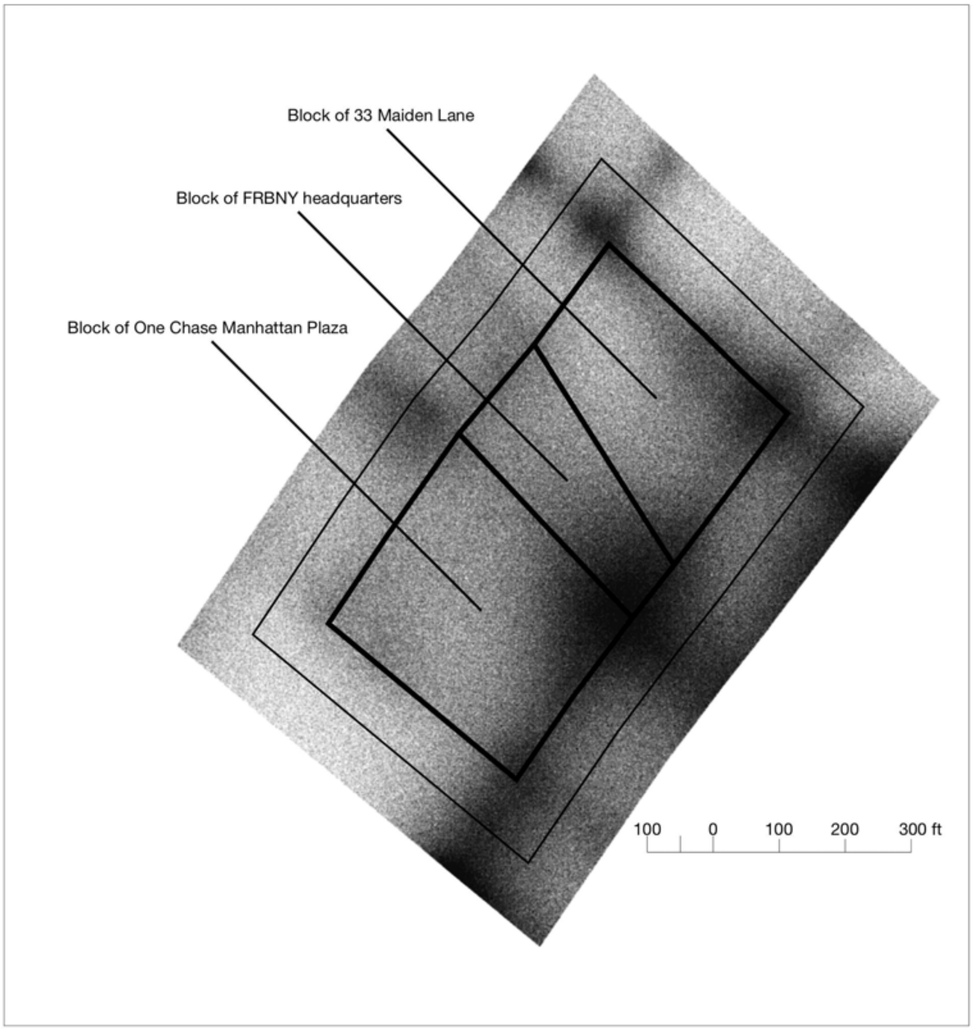
[28] The presence of outliers motivates the use of the median rather than the mean.

[29] The median is calculated over the twenty previous weekdays, including any holidays.

[30] The median is calculated over the twenty previous weekdays in the sample after the removal of holiday periods and vendor discrepancies.

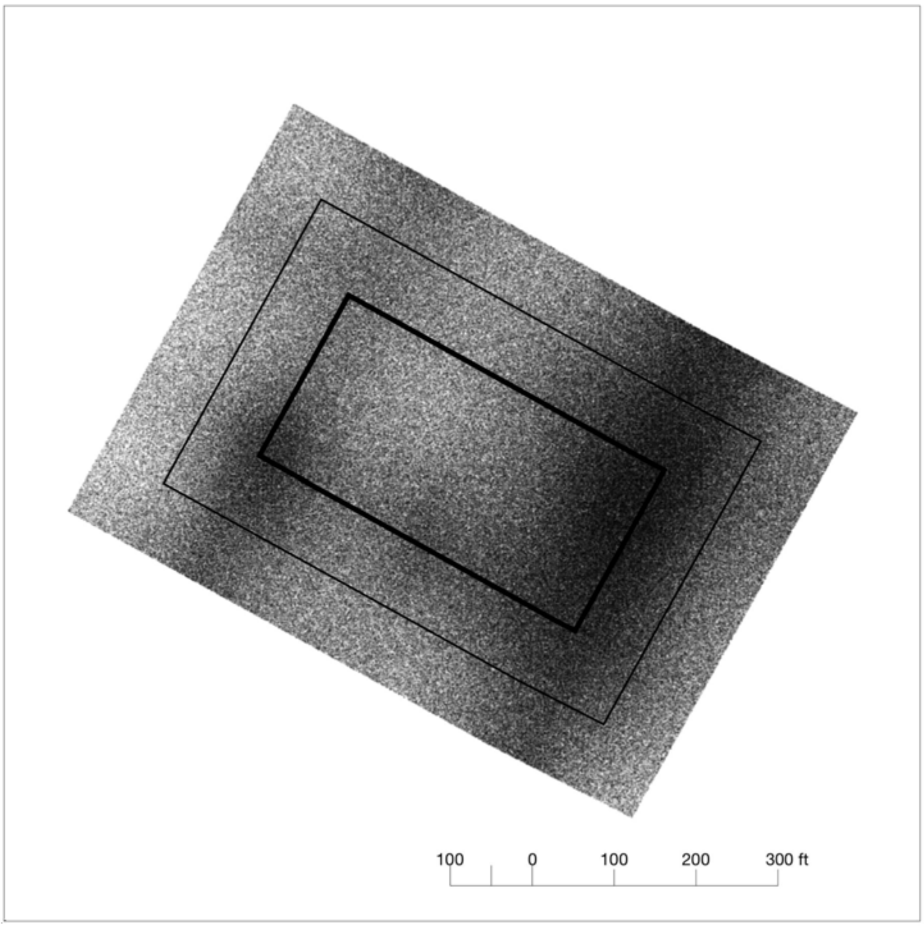
weekdays for which the deviation is at least as negative as the lowest-magnitude deviation during the hurricane periods. The five dates in the set are all associated with disruptive winter weather: 2 March 2009, 10 February 2010, 3 January 2014, 21 January 2014 and 13 February 2014. After their removal, one is left with 1425 weekdays out of the 1565 weekdays from 2009 through 2014, a reduction of 140 days (8.9%).

Figure B.1: Yellow taxi pick-up and drop-off coordinates in the vicinity of the FRBNY



Notes: The borders of the blocks are superimposed and approximately indicate the locations of roads (thick line segments). The thin line segments are an outward shift of the boundary of the three blocks by 100 feet. The data span all rides from 2009 through 2014.

Figure B.2: Yellow taxi pick-up and drop-off coordinates around the block of JPMorgan Chase headquarters



Notes: The border of the block is superimposed and approximately indicates the locations of roads (thick line segments). The thin line segments are an outward shift of the boundary of the block by 100 feet. For greater clarity given the very large volume of rides, the data are random draws of one-tenth of the rides from 2009 through 2014 rather than the full set.