The International Spillover of Monetary Policy Shock: New Evidence from Nighttime Light*

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Abstract

We revisit the spillover effects of U.S. monetary policy using a new nighttime light (NTL) big data as a high-frequency, granular proxy for real economic activity. By merging this data with firm-level information and transaction-level datasets on land auction and bond issuance by Chinese real estate firms, we find that an unexpected U.S. tightening significantly reduces its output via a novel construction channel—NTL fluctuations are primarily driven by non-built-up areas rather than city centers or suburbs. Furthermore, lands purchased by firms with weaker financial conditions, especially those with foreign bond issuance, experience a larger contraction in NTL intensity. Our evidence suggests that this construction channel of U.S. monetary policy spillover applies to other emerging economies.

Keywords: Monetary Policy Spillover, Nighttime Light, Construction Channel, Financing Conditions

JEL codes: E44, E52, F30, F42

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1 Introduction

The cross-border spillover effects of monetary policy constitute a critical research area in both monetary and international economics, particularly regarding U.S. monetary policy as a primary determinant of global financial cycles (Miranda-Agrippino and Rey, 2020). While existing literature has extensively examined impacts on international financial markets (see Bhattarai and Neely, 2022 for a comprehensive review), empirical evidence remains limited concerning: (1) causal effects on real economic outcomes, and (2) the transmission mechanism for monetary policy international spillover.

However, these tasks face several empirical challenges using traditional macroeconomic indicators like GDP.[1] First, their low frequencies imply many confounding factors beyond monetary shocks within such long measurement windows. This extended time frame also exacerbates reverse causality concerns, as observed economic performance may shape subsequent monetary policy decisions. Second, traditional output measures suffer from measurement errors due to misreporting, statistical aggregation, or even political manipulation—a problem particularly acute in emerging markets (see Clark et al., 2020; Henderson et al., 2012; Martínez, 2022, etc. for more details). Finally, additional complications arise from cross-country inconsistencies in accounting standards and the coarse spatial granularity of available data (e.g., city-level GDP without finer subregional breakdowns).

In light of this, we try to employ a proxy of real activity that is at a higher frequency, relatively objective, internationally comparable, and available at any spatial level. An ideal candidate is the geospatial data of nighttime light (NTL), which has been emerging in recent economics studies, and has several advantages that suit our study. First, the data is released at a daily frequency and has been publicly available since early 2012 with an ongoing update. Second, the satellite-related measurement errors are orthogonal to economic activities (Pinkovskiy & Sala-i-Martin, 2016) and are also free of potential

[1] Compared to analyzing impacts on asset prices and yields, examining real economic effects is both more consequential and methodologically challenging, see Swanson, 2021 and Bhattarai and Neely, 2022.

data manipulation (Chor & Li, 2024; Martínez, 2022). Third, the images captured by satellites at night measure the brightness of different places with a uniform lens, avoiding accounting standard differences across administrative boundaries in traditional economic data. Fourth, spatial aggregation is also available at almost any level, enabling the evaluation of policy effects in any selected area and facilitating the identification of the transmission channel.[2]

With the NTL data and monetary shocks in hand, we study the international spillover effects of US monetary policy. In the main part, we take China, the largest emerging market, as an example, where we have detailed spatial level and micro level data to explore the channel.[3] The baseline results come from the Local Projection (henceforth "LP", Jordà, 2005) regressions of China's overall NTL on US MPs. The NTL data are from Visible Infrared Imaging Radiometer Suite (VIIRS) instruments operated by the National Aeronautics and Space Administration (NASA) with a daily frequency. The baseline MPs we use is the 30-minute high-frequency Federal Fund Rate change around FOMC announcements. We aggregate the daily series from 2012 to 2023 to weekly in the baseline to avoid unpleasant noises. Several main findings are shown as follows.

To begin with, we find that the overall NTL negatively responds to the US MPs. The response appears within several weeks right after the shock and the implied GDP decrease by a one-standard deviation of MPs is around 0.8 percent on average. In addition to the aggregate response, the effects also exhibit clear spatial variation across Chinese cities.

We hypothesize that the U.S. monetary policy shocks spill over to the Chinese economy through the construction channel: a tightening of U.S. monetary policy increases the financing cost of Chinese real-estate developers via both domestic bank loans and foreign bonds, which, in turn, reduces the construction activities on the land they purchased.

To test this hypothesis, we first show evidence that U.S. monetary tightening neg-

[2]The GDP-NTL correlation holds when we change the unit of observation from the administrative city or county to arbitrarily chosen areas (Sherman et al., 2023).

[3]In the extension part, we also study the impacts of the US monetary policy on other economies.

atively affects the construction activities by exploiting the spatial heterogeneity of the response of NTLs to US monetary policy tightening at city, subregions of a city and land-parcel levels. Specifically, we begin by aggregating the aggregate nighttime light (NTL) at the city level and show that contractionary effects are more pronounced in cities with higher initial levels of construction activity. We then divide each city into three distinct zones—city centers, suburbs, and non-built-up areas, and compare the responses of NTLs to US MP shocks across these subareas. The results reveal that the overall decline in NTL is primarily driven by reduced activity in non-built-up areas, where construction-related operations are concentrated. Lastly, we provide direct micro-level support for this channel by documenting a post-tightening reduction in NTL intensity within land parcels acquired by real estate developers.

We then demonstrate that real estate firms' financing conditions serve as a crucial transmission mechanism through which US monetary tightening affects China's real economy via the construction channel. To start with, the US tightening significantly worsens the financing conditions of real estate firms, which are usually financially constrained, thus harming construction-related real activities. Consistently, at the micro level, US monetary tightening leads to a decline in real estate firms' revenue and profits. Particularly, using confidential bond issuance data, we observe that the US tightening has significantly limited real estate firms' overseas bond financing.

Besides, in line with this channel, the adverse effects on NTL are more pronounced for more debt-burdened firms. This is especially the case after the 2020, where the three red-line policy was imposed. In terms of the debt structure, we find that firms with greater reliance on domestic bank loans and foreign bond financing undergo a bigger impact. The evidence is also consistent at the regional level. NTL drops are more pronounced in cities where land transactions involve more highly leveraged firms.

Lastly, as further discussions, we first show that US monetary policy also affects the NTL in other economies, especially emerging market countries or regions, with less

urbanized countries more impacted. Secondly, conventional US monetary policy shocks seem to be more effective in affecting foreign real activities than unconventional tools. Thirdly, the spillover effects of the monetary shocks from the European Central Bank and the Bank of Japan are relatively insignificant, which suggests the special role of the Fed's monetary policy in affecting the global business cycle. By comparison, China's own monetary shock could also significantly affect the NTL. Finally, the adverse effects are weaker in a city with a higher net export over GDP ratio, which partially offsets the negative effects.

Literature. In a nutshell, our work differs from conventional studies on monetary policy transmission—which predominantly analyze low-frequency aggregated macroeconomic data—by instead adopting a micro-level lens with high-frequency data and exploiting spatial heterogeneity to uncover the causal impacts of monetary policy and previously underexplored transmission mechanisms.

Specifically, due to the low frequency of output data, people usually employ the VAR approach to empirically study the impact on real activities (e.g. S. Kim, 2001, Maćkowiak, 2007, Bluedorn and Bowdler, 2011, and Georgiadis, 2016; see Bhattarai and Neely, 2022 for a survey). However, this method suffers from several criticisms, such as misspecification, improper identification restriction, and instability (see Rudebusch, 1998 and Miranda-Agrippino and Ricco, 2021 for more discussion). Benefiting from a higher frequency proxy of real activities, we instead use an event-study-based approach, which is commonly used in the literature to study the responses of financial markets (e.g. Nakamura and Steinsson, 2018, Chari et al., 2021, Swanson, 2021, R. Gürkaynak et al., 2022). This method has less concern about the problem of reverse causality and omitted variables, and thus offers a sharper identification of the causal impacts of monetary policy shocks (R. S. Gürkaynak and Wright, 2013). To our knowledge, we are the first to study the effects of monetary policy on the real economy using nighttime light (NTL) as a high-frequency proxy of real activities.

Previous papers usually study the spillover impact at the country level. By contrast, the observation unit of the NTL data is as small as a square cell with about 464 meters on one side, which allows us to explore a finer heterogeneity across cities, sub-city areas, or even firms.[4]

Moreover, leveraging the spatial granularity of NTL (nighttime light) data, we integrate it with regional, firm-level, and transaction-specific datasets to uncover a novel transmission channel: US monetary tightening suppresses emerging market output via construction-sector linkages. Crucially, real estate firms' financing conditions play an important role in this mechanism.

Secondly, our paper relates to the literature on how monetary policy shapes the real estate markets (e.g. Jordà et al., 2015, Ho et al., 2018, Drechsler et al., 2022). Consistent with most of the papers in this strand, we also find that monetary tightening deteriorates the real estate market.[5] More importantly, we go a step further by demonstrating how the real estate market in emerging economies acts as a significant risk exposure through which international financial shocks impact emerging economies' real sectors. Notably, even in economies with stringent capital controls such as China, this channel still works.

Finally, our paper is also part of the emerging studies utilizing the nighttime light (NTL) data.[6] Most of these papers mainly use low-frequency and aggregate NTL data to investigate economic growth or economic development. Instead, we use the high-frequency and disaggregated NTL data to study how the business cycle fluctuates with macro shocks.[7] More generally, the cleaned dataset is also useful for other studies as a

[4]Besides, our approach has two other appealing advantages: (1) The data can be easily extended to other countries. Unlike traditional national accounts, such as GDP, which have different accounting standards across jurisdictions and countries, the NTL data expose all administrative units under the same measurement standard. (2) The NTL is quite objective and irrelevant to the measurement error of traditional economic indicators, originating from reasons such as statistical capacity and potential data manipulations.

[5]As we study the spillover effect, our paper is closer to Ho et al. (2018), who find that the deduction of the US policy rate since the Great Recession has led to a significant increase in China's housing market using a FAVAR model.

[6]For example, Henderson et al., 2012, Pinkovskiy and Sala-i-Martin, 2016, Bustamante-Calabria et al., 2021, Xu et al., 2021, Martínez, 2022, D. Kim, 2022, J. Kim et al., 2022, L. Jiang and Liu, 2023.

[7]Regarding this aspect, we are closer to Chor and Li (2024) who use the high-frequency NTL data

globally-available high-frequency tracker for economic activities.

2 Data and Measurements

To analyze the impacts of US monetary policy spillover and the corresponding mechanism, we use a series of data, including the exogenous high-frequency US monetary policy shock, nighttime light data, and other traditional measurements of real activity. Different from most of the previous literature using only aggregate data, we also take advantage of many micro-level data, such as land transaction data, bond issuance data, and firm balance sheet data, to study the policy transmission from a more granular perspective.

2.1 Monetary Policy Shock

The baseline monetary policy shock (MPs) used in the study is extracted from 30-minute high-frequency changes in federal fund rates around the Federal Open Market Committee (FOMC) meetings, which captures the unexpected part of interest rate changes.[8] FOMC meetings are usually held on average 8 times each year. We focus on the meetings from 2012 to 2023, as the NTL data starts from 2012. 95 scheduled FOMC meetings were held during the period, and the extracted baseline MPs (MP1) is shown in Figure A.1. See Table A.1 for summary statistics. In the extension part, we also use the US unconventional monetary policy shocks and the shocks in other central banks.

2.2 Nighttime Light

The NTL data are from NASA's Black Marble with public access dating back to 19 January 2012. We use the period until the end of 2023. The original data are in daily frequency, which is convenient for event studies to obtain a sharper identification of the policy impacts around FOMC announcements.

The NTL data are quite granular, where a pixel in the digitalized image corresponds

to study the impact of the US-China trade war on the real economy.

[8]This data is from Jarociński (2024), which follows the approach by Swanson, 2021 and extend estimation of the U.S. monetary policy shocks. We also use the shock of Acosta (2022) as a robustness.

to 15 arc seconds out of 360 degrees in both latitude and longitude, converting to 464m on the equator. These cells are small enough to identify economic activities at almost any regional level (e.g. a sub-city area or even a land of a real estate firm), which greatly facilitates the identification of the causal impacts and the associated transmission mechanism.[9]

The data are captured by satellites with the VIIRS (Visible Infrared Imaging Radiometer Suite) instrument, which is the latest and the most accurate version of Suomi Polar-orbiting Partnership jointly by NASA and NOAA.[10] Unlike the previous generation of satellite images for NTL, the DMSP, the VIIRS is time consistent (Gibson et al., 2021), which supports the intertemporal comparison required in the study. It also has no top-coding problems (Bluhm & Krause, 2022), a vital issue when measuring in bright places, such as the city center. The neighboring cells are not autocorrelated (Michalopoulos & Papaioannou, 2018), which enables precisely distinguishing light sources at the cell level. We use the Black Marble VIIRS product VNP46A2, which applies the Bidirectional Reflectance Distribution Function (BRDF) on the raw satellite image. It removes distraction factors such as stray light and moonlight. It also adjusts the satellite angle, which varies daily when the satellite captures the image at the same place. Additionally, the product labels cells contaminated by cloud and snow covers, enabling our further processing to remove such noises.

We use cloud computers to process the big data at the cell level. To conduct city-level analysis, we also generate aggregated daily NTL series for 345 out of 367 cities (prefectures) in mainland China. For each of the 4,332 available days, there are 55,404,633 cells for the whole country.[11][12] The detailed process is in Appendix A.2.2.

[9]Once the NTL of a construction field is identified, it can be matched with the associated real estate firm using land transaction records. The granular nature of these NTL data also allows the matching of NTL to each subarea within a city, namely the city center, the suburb and the nonbuilt-up area according to the spatial boundaries.

[10]For details of the data sources, see Appendix A.2.1. A web-based interface of the VIIRS light map is available at: https://www.lightpollutionmap.info (light pollution map).

[11]The remaining 22 cities are large in area but have relatively small populations and economic activities. The processing time on cloud computers positively correlates with the area processed. Therefore, we drop them off in the processing for budget and time considerations.

[12]When aggregating the geospatial data at the city level, the shape files of the administrative

We match the NTL with MPs data after aggregating them to weekly frequency.[13] This substantially reduces the noise while keeping the frequency sufficiently high to identify the MPs impact on the real economy. Meanwhile, as FOMC is conducted every six weeks on average, converting the daily series to weekly does not have overlapping issues. We assign each MPs value to the week of the FOMC date and interpolate the weeks with no FOMC meetings as having zero shocks.

We illustrate that NTL significantly and positively correlates with traditional economic activity indicators, such as GDP. Figure B.1 shows such associations at annual frequency and the city level. We also display this correlation across periods/industries/countries. See Appendix B for more details.

2.3 Land Transaction Data

To study the transmission channel in a more granular way, we employ land transaction data, which allow us to get the land-level NTL and connect it to a specific real estate firm. This data comes from Land China (www.landchina.com). We manually match each land transaction with a listed real estate firm and connect them to the associated NTL square unit according to the corresponding latitude and longitude. See Appendix A.3 for more details.

2.4 Bond Issuance Data

To identify how exposure to foreign financial market determines the spillover effects of US monetary policy on Chinese real estate firms, we adopt confidential data on bond issuance from Huang et al. (2024). The data match each recorded issuance with a listed real estate firm. For each issuance, we mainly use the information on total amount and the currency of debt. See Appendix A.4 for more descriptions.

boundaries of the cities we use are derived from the official source (National Bureau of Statistics of China, henceforth NBSC) with revisions to show the updated boundaries across cities in 2022.

[13]Every week is defined as from a Sunday to the closest upcoming Saturday (included).

2.5 Other Data

Apart from the data shown above, we also use the firm-level balance sheet data, regional (city/province) economic indicators, the national account records from China and other countries, financial market data, news shock data, weather data, etc. For more details, see Appendix A.5.

3 The Spillover Effects and the Construction Channel

We adopt the local projection (LP, Jordà, 2005) method to estimate the spillover effects of U.S. monetary policy shocks. Our regression is on the weekly frequency. The tight window helps to isolate the impacts of policy surprise from other confounders and mitigates the concerns of simultaneity. Section 3.1 discusses the average spillover effects of US monetary policy shocks. Sections 3.2 and 3.3 identify the transmission channel from U.S. MP shocks to Chinese economy by exploring heterogeneity of NTL responses across cities and subareas within a city.

3.1 The average effects of U.S. monetary policy shocks on NTLs

Specifically, we apply the following regression equation for our baseline specification.

$$y_{t+h} - y_{t-1} = \alpha^{(h)} + \sum_{q=1}^{Q} \phi_q^{(h)} \Delta y_{t-q} + \sum_{m=0}^{M} \beta_m^{(h)} x_{t-m} + \sum_{r=1}^{R} \gamma_r^{(h)} W_{t-r} + \tau_t + u_{t+h|t} \qquad (1)$$

where y_t is log NTL in week t, Δy_t is the change in log NTL in week t relative to week $t-1$, x is the high-frequency federal fund rate shock around the FOMC announcement.[14] We use AIC criteria to choose the lags of the dependent variable and the shocks.[15] In the extended specifications, we add controls as W and time fixed effects as τ_t. The key underlying assumption here is that the change in NTL is mainly affected by US MPs in

[14] We only study the effects of conventional monetary policy here. The comparison with unconventional monetary policy will be discussed later.

[15] Using the BIC criteria produces the same results.

such a short window around the FOMC meetings, and this effect is orthogonal to other factors.

Applying the equation for $h = 0, \cdots, H$, the IRF is obtained from $\{\beta_0^{(0)}, \cdots, \beta_0^{(H)}\}$. We look up to $H = 20$ for the weekly series. The coefficients of the baseline LP regressions are shown in Figure 1.

There are several takeaways from our baseline results: (1) Using a high-frequency specification, we confirm that the US monetary policy tightening negatively affects China's real activities, which is consistent with previous literature (e.g. S. Kim, 2001, Maćkowiak, 2007, and Bluedorn and Bowdler, 2011, etc.). Worth noting that the impact of monetary tightening on foreign output is more ambiguous than in the domestic context.[16] (2) People tend to believe that monetary transmission, especially cross-border spillover, is lagged. Usually, foreign real activity is assumed to be affected by US interest rate shocks by a lag of one quarter (Uribe and Yue, 2006). Our results suggest this lag seems to be shorter in terms of NTL. (3) The magnitude of the shock on the real economy is material. A unit of the US MPs tightening shock declines China's NTL by 1.02 log points on average within 20 weeks. The correlation of NTL and GDP we obtain is 0.49, and the standard deviation of the shock is 0.016 from 2012 to 2023 (our sample period), implying a one-standard-deviation shock would cause a 0.80 percent drop in China's weekly output.[17]

In the following, we will illustrate that our baseline finding aligns with a construction channel through three pieces of evidence by exploiting the responses of NTLs at different levels: (1) At city level, we find that cities with more construction activities have a larger

[16] Conventional wisdom suggests that contractionary U.S. policy should dampen economic activity through reduced American household expenditure and consequent declines in import demand from trading partners. However, countervailing effects emerge through exchange rate channels - dollar appreciation may enhance purchasing power for dollar-holders, potentially stimulating import demand. Furthermore, the effects of financial channels add substantial complexity to this transmission. The relative dominance of trade versus financial spillovers remains contested in theoretical discourse, highlighting the need for additional empirical evidence to answer these debates.

[17] Our results remain robust across various validations, including adding year-quarter fixed effects, alternative shocks, bootstrap standard errors, different model specifications, and additional controls for confounding factors such as US news shocks, weather conditions, and US-China tensions. See Appendix C for more details.

impact; (2) We then compare the responses of NTLs among three subareas within a city: city centers, suburbs, and non-built-up areas. It is seen that the overall negative responses of NTL are driven by the reaction in non-built-up areas that feature construction-related activities. (3) Then, from a micro perspective, we directly verify this channel by showing that the NTL in lands purchased by real estate firms declines after a tightening shock.

3.2 Heterogeneity across Cities

We conjecture that if the NTL responses reflect a construction channel, cities that have more construction activities should be more affected. To verify this, we used the urban constructed rate as a proxy for the intensity of construction. For each city, the urban constructed rate is defined as the percentage of the area constructed with urban infrastructure, including buildings and other human facilities. Usually, cities with lower urban construction rates should be more involved in construction-related activities. To quantitatively associate the urban constructed rate with the responses to US MPs, we identify with a city-level panel of NTL, US MPs, and urban constructed rate. The regression equation is as follows.

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^{(h)} + \sum_{q=1}^{4} \phi_q^{(h)} \Delta y_{i,t-q} + \beta_1^{(h)} s_{i,t-L} + \beta_2^{(h)} x_t s_{i,t-L} + \gamma^{(h)} W_{i,t-L} + \tau_t^{(h)} + u_{i,t+h|t} \tag{2}$$

Here $y_{i,t}$ is the log NTL in the city i in week t. x_t is MPs in week t. $s_{i,t}$ is the urban constructed rate in city i in week t.[18] W denotes a series of control variables, including lagged population, GDP, and urban district area, and their interaction terms with the MPs. In robustness check, we will also control weather conditions. α and τ are fixed effects for city and week, respectively. To exclude potential endogeneity, the urban constructed rate used in the regression is lagged by L. We choose the length of the lag as one year in the baseline. The estimates of the key coefficient are $\beta_2^{(h)}$ and the IRF of each horizon h is displayed in Figure 2. We find that the coefficients of interaction terms are overall significantly positive, which indicates that a city with a lower urban

[18] In the baseline, the urban constructed rate is updated on an annual basis. Therefore, the value used depends on the year in which the week t is located.

constructed rate is more negatively affected by the US tightening. The results are almost similar using the urban area rate (see Figure D.3).[19] Consistently, we find that cities that experience higher growth in recent land transactions are also more affected by the US tightening because construction-related activities are more heavily involved in these cities. The results are shown in Figure D.4.

Since the intensity of construction activities might be influenced by whether conditions, another test of the construction channel is to compare the differential responses of NTLs to US MP shocks between summer and winter. For example, in some northern parts of China, construction fields do not operate in winter due to extremely low temperature, and NTL from construction activities should respond less to the US tightening than during the summer. This contrasts to the south region, where the intensity of construction activities should be less affected by seasons. To test this, we split our sample into cities in the north and south regions of China when aggregating NTL at the city level.[20] We further divide the sample period into the summer period and the winter period. The summer period is from April to September. The winter period is October to March in the next year.

As shown in Figure 3, for the northern region, the NTL responses to US MPs in the summer are significant, while the response in the winter is statistically indifferent from zero. In contrast, for the southern region, the difference across seasons is relatively weaker than that in the north (see Figure D.5).[21]

[19]For each city, the urban area rate is defined as the percentage of the administrative area that is built up. Using the ratio of population in urban areas as a proxy of urbanization rate produces qualitatively consistent results. Our estimations are also robust to weather controls. These results are omitted for space saving and are available upon request.

[20]The division here follows the official definition of NBSC.

[21]To compare the different response seasonality between the north and the south, we apply a triple interaction identification: $y_{i,t+h} - y_{i,t-1} = \alpha_i^{(h)} + \sum_{q=1}^{4} \phi_q^{(h)} \Delta y_{i,t-q} + \beta_1^{(h)} x_t + \beta_2^{(h)} \mathbb{1}(\text{North}_i) + \beta_3^{(h)} x_t \mathbb{1}(\text{North}_i) + \beta_4^{(h)} x_t \mathbb{1}(\text{Summer}_t) + \beta_5^{(h)} \mathbb{1}(\text{North}_i) \mathbb{1}(\text{Summer}_t) + \beta_6^{(h)} x_t \mathbb{1}(\text{North}_i) \mathbb{1}(\text{Summer}_t) + u_{i,t+h|t}$, where i is the province. We expect β_6 to be negative.

3.3 Heterogeneity across Subareas Within a City

Another way to test the construction channel is to examine the heterogeneous responses of NTLs in different subareas within a city. In particular, we decompose a city into the city center, the suburbs, and the non-built-up areas, which may proxy for service-related, manufacturing, and construction activities, respectively. Hence, if the construction channel is a main driver, we expect that the average effect of US MPs on NTL across cities is mainly driven by the response of non-built-areas.

For each city, we identify the built-up areas in different years using the boundary of satellite images (H. Jiang et al., 2022) and the corresponding non-built-up areas that exclude uninhabitable lands defined by the land cover map from the China Land Cover Dataset (CLCD). The percentage of built-up area identified by the geospatial data is positively correlated with the urban constructed rate from NBSC, as shown in Figure D.2. We define the city center as the area built in 1990, the suburb as the area built up in 2010 but not in 1990, and the non-built area as other parts.[22] We choose 2010 as the threshold year because the NTL series starts from 2012, therefore excluding potential endogeneity issues.[23] We illustrate the division of the city center, the suburb, and the non-built-up area for selected cities in Figure 4.

The heterogeneous responses by areas are shown in Figure 5. It shows that the effects on non-built-up areas are quite significantly negative, driving the overall responses. The NTL in non-built-up areas mainly reflects the real activities of construction, such as the light from construction sites at night and from new buildings. Intuitively, the US tightening could quickly worsen China's financial markets and later deteriorate real estate firms' operations[24], which would lead to a delay, a slowdown, or even stagnation in the construction works. During a housing market boom, real estate developers incentivize

[22] We confirm the validity of the identification after manually checking the identified centers and suburbs for major Chinese cities, including Beijing, Shanghai, Guangzhou, Shenzhen, and Hangzhou. The identification closely matches the conventional definition of centers and suburbs in these cities.

[23] The results are robust when we define the suburb as the area built up in 2015, but not in 1990. See Figure D.1.

[24] Evidence will be provided in Section 4.

construction firms to accelerate production, allowing for faster home sales and improved cash flow. This often leads to extended work hours (including night shifts) and a higher volume of completed housing units, resulting in increased light emissions at night. In contrast, following US monetary tightening and subsequent market downturns, this dynamic reverses. By comparison, the impacts are insignificant for the centers and suburbs, the NTL of which mainly implies service and manufacturing activities, respectively.

4 Role of RE Developers' Financing Conditions for the Spillover of US MPs

So far, our findings indicate that US monetary shocks transmit to China's real economy through a construction channel. We now further identify the role of financing conditions of real estate firms in the transmission of US MPs to construction activities. To this end, we link each land parcel to a real estate firm and explore the response of NTLs for land parcels purchased by real estate firms subject to different financing constraints. Section 4.1 estimates the average responses of NTL of land purchased by RE firms. Section 4.2 explores the heterogeneous responses of NTLs across firms. Section 4.3 illustrates the aggregate implication at a city level.

4.1 Average Responses of NTL in Lands Purchased by Real Estate Firms

To start with, we estimate the average response of the NTL of lands purchased by real estate firms to US monetary policy shocks. These lands are very likely to be construction fields, and 86 percent of them are located in the non-built-up areas of the city. For each land that we can associate with a listed firm, we geolocate the coordinates of the land by reverse geocoding the textual address.[25] Figure 6 shows a city-level illustration of the

[25]The API we use is Amap. For each observation, the input is the textual address, the city, and the province. The output is longitude, latitude, and the implied textual address. To exclude excessively rough results, we filter out outputs with textual addresses ending with a city or county name or being less than 16 characters.

percent of the geolocated transacted lands in the non-built-up area. In most cities, the transacted land in the non-built-up area account for more than 80 percent of all such land.[26] Then, for each identified coordinate, we use the NTL of the cell that includes the location as the proxy for the light of the transacted land.

To directly examine the changes in NTL on the land associated with real estate firms, we aggregated the NTL of all the corresponding cells and identified the response to MPs using our baseline specification. The IRF of the NTL of the aggregated transacted lands is in Figure 7. The NTL in land traded by real estate firms decreases after the US tightening. This is consistent with our baseline, which implies that the response of the construction works is a driver of the overall decrease in NTL.

4.2 Roles of RE Firms' Financing Conditions

If construction activities are constrained by deteriorating financing conditions, real estate firms with weaker financial positions are likely to experience more severe impacts. We take the following steps to verify this conjecture. First, we show that both RE firms' bank loans and their foreign bonds issuance declines in response to US MPs. Second, we show that NTLs for land purchased by RE firms with higher leverage ratios are more negatively affected. And this is especially true for the period with the three-red-line policy implemented.

4.2.1 Impacts on External Finance

Using confidential bond issuance data from Huang et al. (2024) (see Appendix A.4 for more descriptions), we explore whether US MP tightening has a negative impact on bond issuance by real estate firms. The specification is as follows.

$$\left(\frac{\text{Net Bond Value Standing Value}}{\text{Operation Indicator}}\right)_{i,t} = \beta_1 x_t + \alpha_i + \varepsilon_{i,t}. \tag{3}$$

[26] Among the 265 cities with geolocated land transactions, only 54 have less than 80 percent of the lands in the non-built-up area, and only 12 have less than 60 percent of the lands in the non-built-up area.

Here, i is firm, t is month, and α_i is the firm FE. The point estimate to look at is β_1. We scale net standing value of a firm's bonds by its size, as represented by asset, liability, current liability, or long-term liability.

We find that the US tightening significantly impedes foreign bond financing of real estate firms, especially with regard to short-term debt (See Table E.1 Panel A), while the domestic bond financing is not significantly impeded (See Table E.1 Panel B). Using a same specification, it is also found that firms' interest expenses significantly increase after a tightening shock, indicating a bigger debt burden (See Table E.2).

4.2.2 Role of Financing Conditions

To identify the role of financing conditions, we first examine whether firms with a higher debt burden are more sensitive to US monetary tightening by looking at the NTL change of the lands purchased by real estate firms. The specification is

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^{(h)} + \sum_{q=1}^{4} \phi_q^{(h)} \Delta y_{i,t-q} + \beta_1^{(h)} x_t + \beta_2^{(h)} x_t s_{i,t-L} + \gamma^{(h)} W_{i,t-L} + u_{i,t+h|t}. \quad (4)$$

Here, s is the dummy of firm i's debt ratio in the last quarter (denoted by the lag operator L) to exclude potential endogeneity issues. The control variables in W include the lagged asset and profit ratio of the firm, and their interaction terms with MPs. We classify a firm as having "High Debt Ratio" if the firm has a debt ratio higher than the median of all firms in a given quarter. The coefficient of the interaction term of US MPs and the debt ratio dummy is in Figure 8. It is overall negative, which indicates that the NTL of a firm with a higher debt ratio is more impacted by the US tightening.

To connect the operation performance of real estate firms with activities in the construction sector, we also look at the account payable of real estate firms, where a considerable proportion comes from the accounts receivable of construction firms. We use the identification of the debt ratio above. As shown in Figure 9, real estate firms with a higher charge of accounts payable, reflecting more difficulties in financing their construction projects, are more sensitive to US monetary tightening.

The "Three-red-line" policy was introduced by the People's Bank of China (PBC), the China Banking and Insurance Regulatory Commission, and other governmental institutions in China to control the overwhelming debt of real estate firms to prevent potential financial risk. It was implemented on August 20th, 2020. The three red lines of real estate companies are measured as follows: (1) $\frac{\text{Liability}-\text{Presales Revenue}}{\text{Asset}-\text{Presales Revenue}}$; (2) $\frac{\text{Interest-bearing Liability}-\text{Cash}}{\text{Equity}}$; (3) $\frac{\text{Cash}}{\text{Short-term or Maturing Interest-bearing Liability}}$. For the first two indicators, the acceptable upper limit is 0.7 and 1, respectively. For the third indicator, the acceptable lower limit is 1. Those cross-line firms will experience a harsher financing restriction per this policy. Therefore, to examine the role of financing conditions, we expect that for those firms violating the red lines, the responses of NTLs to US MPs would be more negative after the three-red-line policy was implemented, while this might not be true for those RE firms not violating the red-lines (control group). The specification is as follows:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} =& \alpha_i^{(h)} + \sum_{q=1}^{4} \phi_q^{(h)} \Delta y_{i,t-q} + \beta_1^{(h)} x_t \\ &+ \beta_2^{(h)} x_t \mathbb{1}\left(\text{After Policy Implementation}_t\right) + \gamma^{(h)} W_{i,t-L} + u_{i,t+h|t} \end{aligned} \tag{5}$$

where $\mathbb{1}\left(\text{After Policy Implementation}_t\right)$ equals 1 if after the implementation of policy. We run the regression separately for firms that cross the red lines and firms that do not cross the red lines.[27]

Figure 10 plots the differential impacts of US MPs on NTLs for the two types of real estate firms between the policy period and pre-policy period. Consistent with our conjecture, the left panel shows that the coefficient of the interaction term is overall significantly negative for firms that cross the red lines, suggesting that firms that cross the lines (supposed to face stricter financing restrictions) are more affected after the "three-red-line" policy was implemented. In contrast, the coefficients of the interaction term are mostly insignificant for firms that did not cross the three red lines. A comparison of these two panels suggests that financial tightening plays an important role in the transmission of US MPs into NTLs of land purchased by real estate firms.

[27]Here, we define a firm as crossing the red lines if it crosses any of the three red lines on the quarter before the policy implementation date (i.e., 2020Q2).

4.2.3 Role of Debt Categories

We would like to further identify the specific financing vehicles through which US monetary tightening affects the construction activities by real estate firms. A real estate firm's overall debt consists mainly of domestic loans, domestic bonds and Foreign bonds. A US monetary tightening would lead to an increase in interest payment for all these debt categories via different markets. To assess the importance of individual debt categories for the spillovers, we use the following specification.

$$
\begin{aligned}
y_{i,t+h} - y_{i,t-1} = \alpha_i^{(h)} &+ \sum_{q=1}^{4} \phi_q^{(h)} \Delta y_{i,t-q} + \beta_1^{(h)} x_t \\
&+ \beta_2^{(h)} x_t \mathbb{1}\left(\frac{\text{Foreign Bond Standing Value}_{i,t-1}}{\text{Asset}_{i,t-L}} > \text{P50} \right) \\
&+ \beta_3^{(h)} x_t \mathbb{1}\left(\frac{\text{Domestic Bond Standing Value}_{i,t-1}}{\text{Asset}_{i,t-L}} > \text{P50} \right) \\
&+ \beta_4^{(h)} x_t \mathbb{1}\left(\frac{\text{Domestic Loan Standing Value}_{i,t-1}}{\text{Asset}_{i,t-L}} > \text{P50} \right) \\
&+ \gamma^{(h)} W_{i,t-L} + u_{i,t+h|t}
\end{aligned}
$$

The IRFs of β_2, β_3 and β_4 are in Figure 11.[28] The top right panel shows that firms issuing more foreign bonds are more exposed to US monetary tightening since week 6 (β_2 is significantly negative overall). Similarly, firms that issue more domestic loans also have experience a more negative response to US monetary tightening. By comparison, the coefficient of domestic bonds is not very significant.[29] This suggests that US monetary tightening affects negatively the construction activities mainly through an increase in the financing cost of domestic loans and foreign bonds.

4.3 City-level Exposure to Financially-troubled RE Firms

Our firm-land-level empirical analysis suggests that the US tightening has a negative impact on the NTLs of land purchased by financially troubled real estate firms. In

[28] The upper left panel is the result in Figure 8. We put it here for comparison. β_2, β_3 and β_4 are displayed in the upper right, bottom left, and bottom right panel, respectively.

[29] After around 12 weeks, the coefficient of domestic bond is slightly positive, which seems to indicate that firms issuing more domestic bonds experience a weaker effect. This is plausible because firms may issue more domestic bonds to offset the financing limitation originating from foreign adverse shocks.

this section, we would like to demonstrate that this channel bears important aggregate implications. In particular, we would like to show that the impacts are bigger for cities with more land purchased by those real estate firms with financial troubles.

For each city, we define the "bad deal index" as the product of land transaction growth and the aggregated liability ratio. For each city in each year, we identify the listed firm associated with each land transaction. Then, we obtain the financial condition of the corresponding listed firm for each land transaction. In this way, we obtain the associated financial condition for each land transaction. When aggregating the associated financial conditions to the city level, we weight each transaction by either revenue or area of the transaction.[30] A higher "bad deal index" signifies more troubled land transaction in the city. For example, in 2020, the top 10 cities with the highest "bad deal index" are: Jilin, Guangyuan, Chongzuo, Zhaotong, Tongchuan, Jincheng, Yingtan, Dandong, Liaoyuan and Suihua. In our land transaction data, the real estate firms with the top 10 highest land auction revenues from these cities are: Evergrande, Country Garden, Greenland, Seazen Group, Gemdale, China Everbright Group, Seazen Holdings, Wuzhou Property, Eurasia Group, and Henderson Land Group.

We use the empirical specification Equation 2 [31]. We find that NTL in cities with a higher "bad deal index" declines more after a US tightening, as shown in Figure 12.[32]

To summarize, our main empirical findings are as follows: (1) the US monetary tightening has a negative impact on real estate firms' financing conditions via their foreign bond issuance and domestic bank loans. (2) NTLs for land purchased by real estate firms with higher leverage respond more negatively to U.S. monetary tightening. In particular, firms with greater reliance on domestic bank loans and foreign bonds undergo a greater impact. (3) Accordingly, impacts are also more pronounced for cities with more exposure

[30] The land transaction growth measurement is either area or revenue and should be the same as the aggregation weighting. To incorporate lagged impact, we use the three-year moving average for both factors.

[31] Control variables include city-level lagged population, floor space wait-to-sale ratio, and the ratio of real estate investment over GDP, and their interaction terms with the MPs.

[32] The result from weighting by revenue is robust to weighting by area when aggregating from land-level to city-level, as shown in Figure E.1.

to land purchased by real estate firms with worse financing conditions.

5 Further Discussion

5.1 International Comparison

We extend our results to all economies in the world using monthly NTL data pre-processed by Earth Observation Group (Colorado School of Mines, 2024).[33] The results are in Figure 13. It is seen that the US tightening has almost negative effects throughout the world with a bigger impact on emerging economies than on advanced economies, which is in line with previous literature (e.g. Bräuning and Ivashina, 2020, Dedola et al., 2017). Among emerging markets, the effects are more prominent for those economies with rapid urbanization in Asia and Africa, which is consistent with our construction channel. Besides, using a specification similar to Equation 2, we find that economies with lower population urbanization rates have stronger negative responses to the US MPs (Figure F.1). The coefficient of interaction term between MPs and urbanization rate is overall positive.

Apart from using monthly data for all the economies, we also selected several of mainland China's neighbors employing weekly NTL, which is more similar to our baseline analysis on China.[34] The results are in Figure F.2. The conclusion is consistent that emerging markets are usually more sensitive than advanced economies.[35]

[33]The VIIRS data covering all the world area starts from 2014. Therefore, we use the VIIRS instrument data since 2014. For months before 2014, we use the DMSP instrument data and match the trends with a conversion DMSP-to-VIIRS factor. The conversion factor is based on annual VIIRS and DMSP instrument data in 2012.

[34]The processing of weekly data is very time-consuming, so we only chose several economies for illustration. Emerging market economies include China, Mongolia, Vietnam, Thailand, Bangladesh, and India while advanced economies include Hong Kong (China), Macau (China), Taiwan (China), South Korea, Japan, and Australia.

[35]However, we should be cautious to interpret this difference between EM and AE as the real activities featured in these two types of economies are different. For example, urbanization and night shifts, two important sources of NTL in EM, are not pervasive in AE. By comparison, in advanced countries, NTL is more reflected in service activities at night, such as the operation of entertainment venues. Consequently, the transmission channel may differ from the one we proposed, which calls for future exploration.

5.2 Conventional versus Unconventional Monetary Policy

To compare the effects of conventional monetary policy (CMP) and unconventional monetary policy (UMP), we test the impacts of target shock (close to the federal fund rate shock in the baseline), forward guidance shock (or called Odyssean forward guidance, close to the path shock in R. Gürkaynak and Sack, 2005), Large-scale asset purchase shock (LSAP), and information shock (or called Delphic forward guidance). These shocks are decomposed by Jarociński, 2024 and are shown in Figure F.3. The comparison is displayed in Figure 14. It is found that only targeted FFR tightening shock has a significantly negative impact on NTL, but not forward guidance, LSAP or information shocks, which suggests that the conventional monetary policy seems to be more effective in affecting real output.

5.3 MPs of China and Other Economies

Apart from MPs by the Fed, we also study the impact of MPs by other major central banks, such as the People's Bank of China (PBC), European Central Bank (ECB), and the Bank of Japan (BOJ) on the real economy in China, as shown in Figure F.4.[36] Specifically, we apply the baseline LP identification and replace US MPs with the shocks by PBC, ECB, and BOJ. The IRFs are in Figure 15.

As for China's own monetary policy shock, we find similar effects to those of the US shocks. This is plausible as China's tightening could also aggravate the financing conditions of Chinese firms and harm their real activities. Besides, compared with the Fed, the MPs by ECB and BOJ have less impact on the Chinese economy and the coefficients are overall insignificant. These results are consistent with previous literature such as Miranda-Agrippino and Nenova (2022) which documents that the US monetary policy is more effective in influencing other countries than ECB shocks. This makes sense as the US dollar constitutes a dominant role in international trade and financial transactions (Gopinath et al., 2020) and the US monetary policy is a key driver of the

[36]The PBC shock is obtained from Shieh (2024). The ECB shock is identified from Miranda-Agrippino and Nenova (2022). The BOJ shock is identified from Kubota and Shintani (2022).

global finance cycle (Miranda-Agrippino and Rey, 2020). Moreover, China's exchange rate is partially pegged to the US dollar, which may enhance the spillover effects from the US monetary policy.[37]

5.4 Trade Exposure

Although the overall negative responses are driven by the construction channel, we find that trade exposure could mitigate these adverse impacts — cities with higher trade exposure are less negatively impacted by a contractionary US MPs. Intuitively, a positive US MPs will depreciate the Chinese Yuan against the US Dollar (see Figure F.5), which will potentially boost the export.

The specification is the same as the urban constructed rate regression (Equation 2), except for replacing the urban constructed rate indicator with the net export share. We use net export share in the last year as the proxy for net export share to preclude endogeneity issues. The key coefficient estimate is β_2. The IRF of β_2 obtained from varying h from 0 to 10 is in Figure 16. It is seen that the interaction term is overall positive, which suggests that cities with a higher net export share have a smaller adverse impact from the US MPs.

6 Conclusion

This study leverages high-frequency nighttime light (NTL) big data to examine the real economic effects of U.S. monetary policy shocks (MPs) on China. Using an event-study approach, we find that unexpected U.S. monetary tightening exerts an overall contractionary effect on China's real economy. This high-frequency NTL data allows for sharper identification of policy effects and finer dynamic responses compared to traditional low-frequency measures. Additionally, we exploit spatial heterogeneity to uncover differential impacts across city centers, suburbs, and non-built-up areas. Notably, we identify a new

[37] We also test the corresponding path shocks for each central bank, and don't find significant effects either.

transmission channel: U.S. monetary tightening reduces output in China by dampening construction-related activity in non-built-up areas. In addition to the decomposition, this channel is also supported by firm/city-level evidences. Consistent with this mechanism, we also show that real estate firms' financing conditions play a key role in propagating U.S. shocks to China's real economy. Besides, our approach circumvents concerns about official data quality and cross-country statistical discrepancies, facilitating more comparable estimates of U.S. monetary spillovers globally.

Our paper is the first attempt to introduce high-frequency NTL data into the study of monetary economics and revisit several classical questions in this area. We believe in the future this data could also be employed in other research where a high frequency of real economic activity measurement is needed, especially for emerging markets where the NTL is closely related to output. Admittedly, we only use NTL data to explore one of the mechanisms and some other channels like consumption and trade channel, which calls for future investigation.

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Figures

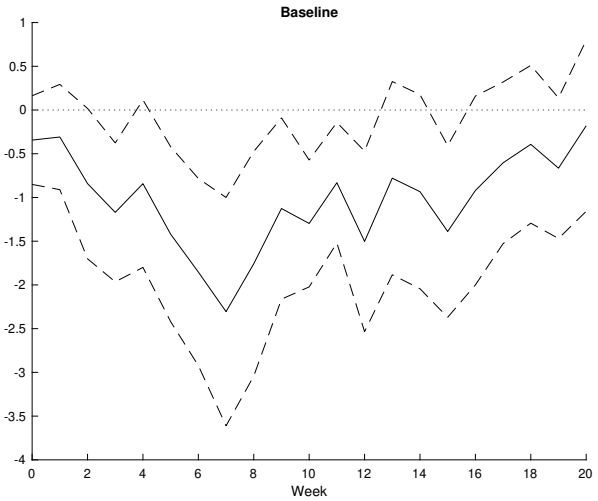


Figure 1: Local Projection of NTL on US MPs: Baseline

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

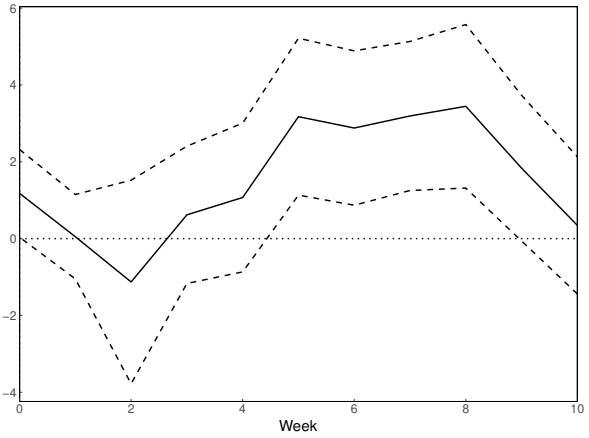


Figure 2: NTL Response to Interaction of US MPs and Urban Constructed Rate, City level

Notes: The dashed ribbons are the 90 percent confidence intervals generated based on standard errors clustered to city and week.

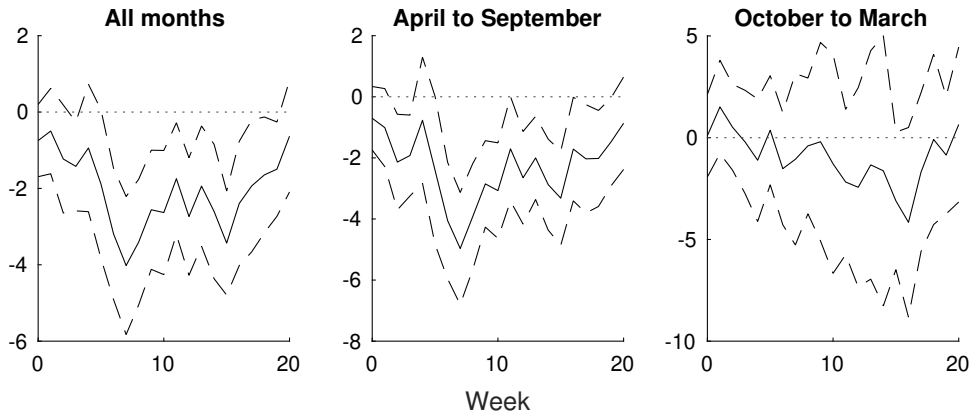


Figure 3: Local Projection of NTL on US MPs: North, Summer vs Winter Periods

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

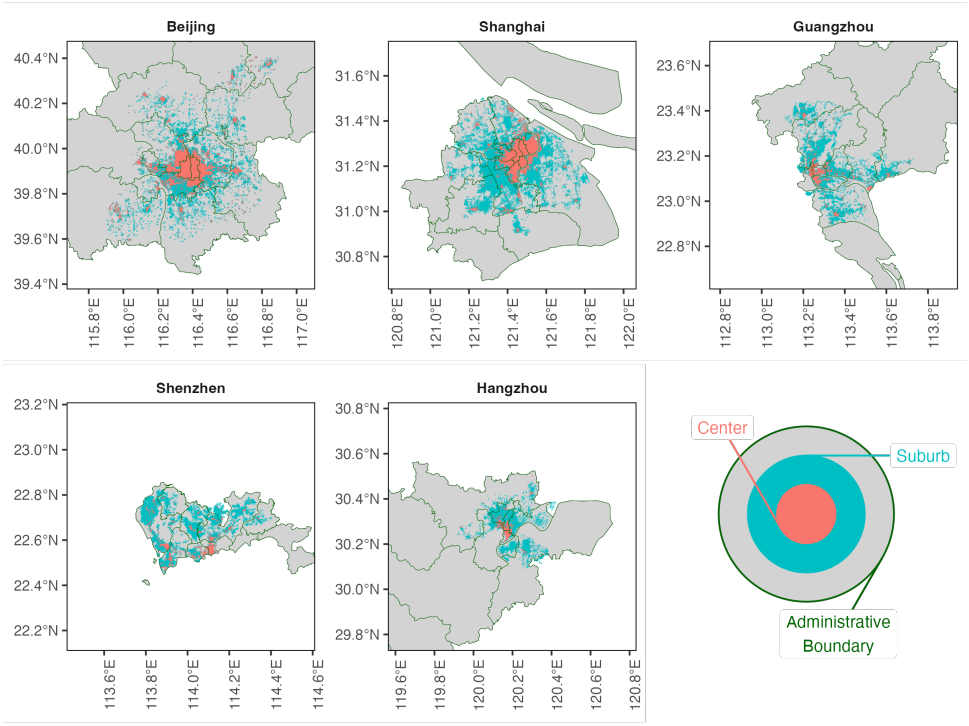


Figure 4: Built-up Areas of Selected Cities

Notes: The boundaries of the built-up areas are identified up to 2010.

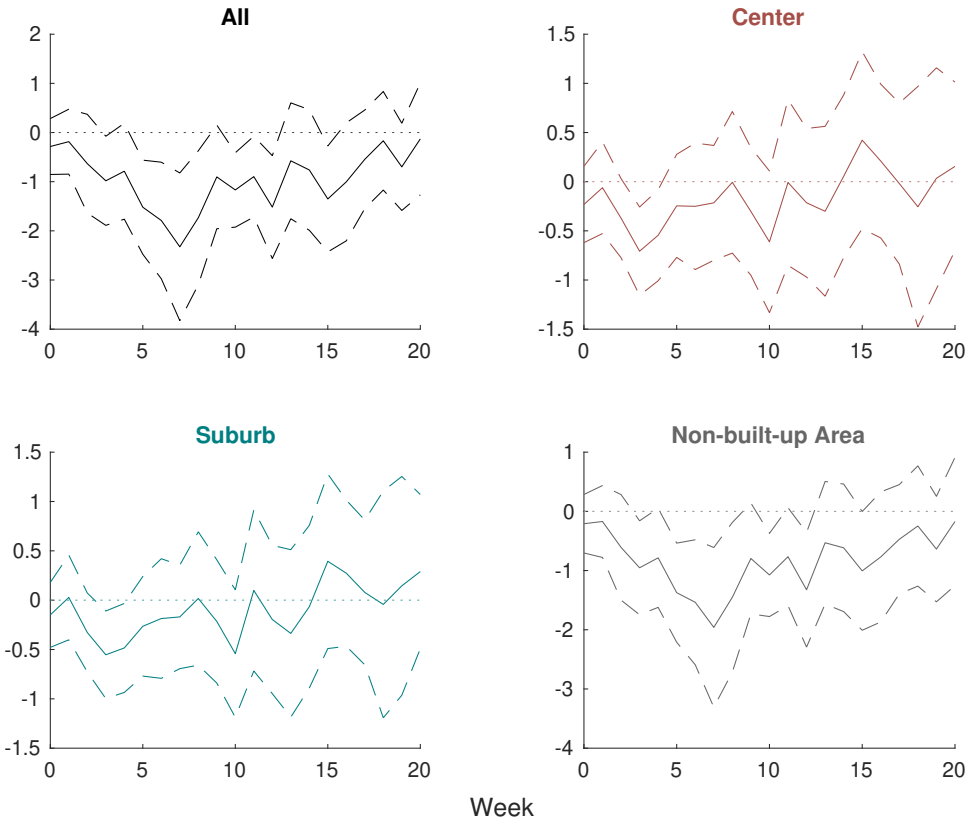


Figure 5: Local Projection of NTL on US MPs: City Areas

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

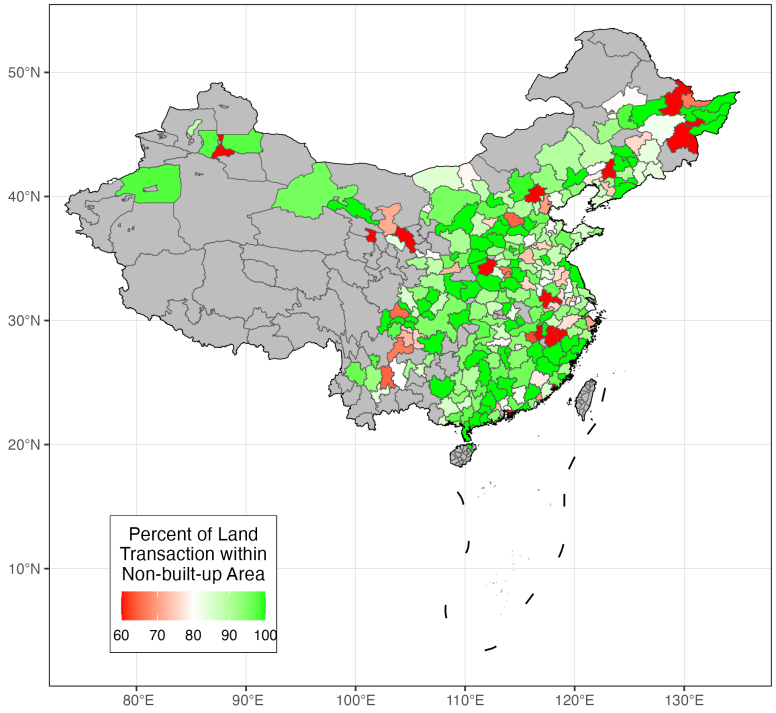


Figure 6: Percent of Transacted Lands in the Non-Built-up Area by City

Notes: Extreme values less than 60 percent are winsorized on the map.

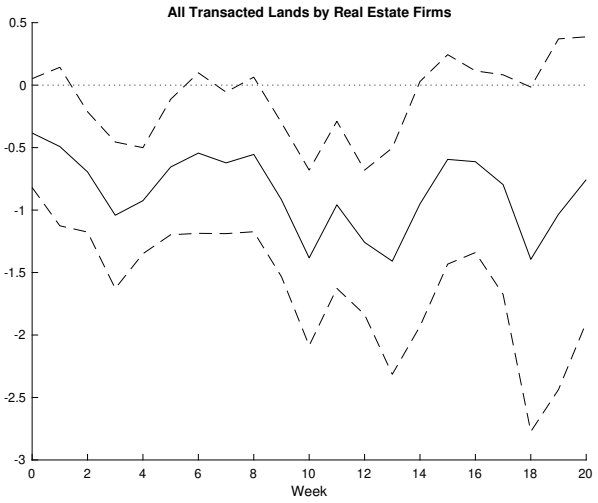


Figure 7: Local Projection of NTL in Transacted Land on US MPs: All Transacted Lands by Listed Real Estate Firms

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

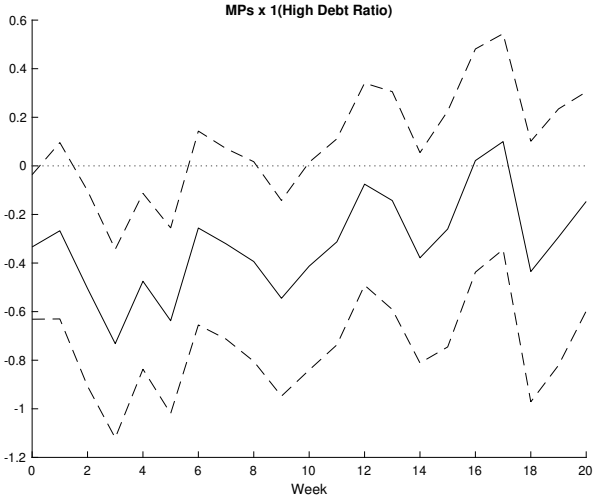


Figure 8: Response of NTL in Transacted Land to US MPs: RE Firm High-Debt-Ratio Dummy

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors clustered to firm and week.

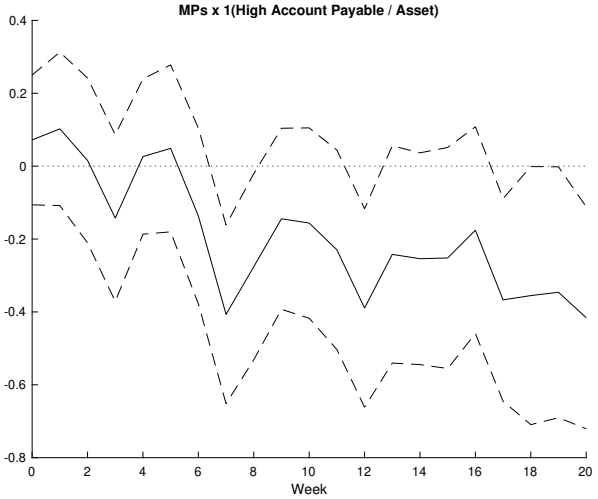


Figure 9: Response of NTL in Transacted Land to US MPs: Account Payable of Associated RE Firms

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors clustered to firm and week.

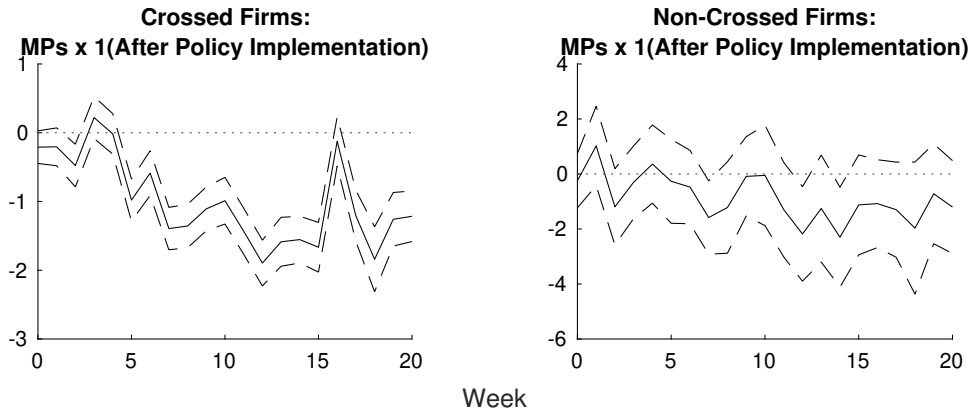


Figure 10: Response of NTL in Transacted Land to US MPs: Before and After the Three Red Line Policy Implementation, Red Line Crossed Firms versus Non-Crossed Firms

Notes: The sample period is from 2018-02-20 to 2023-02-20 (included) with a 5-year window around the policy implementation date. A week is included if the Monday of the week is within the sample period. MPs is aggregated to the weekly frequencies consistent with the dependent variable. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors clustered to firm and week.

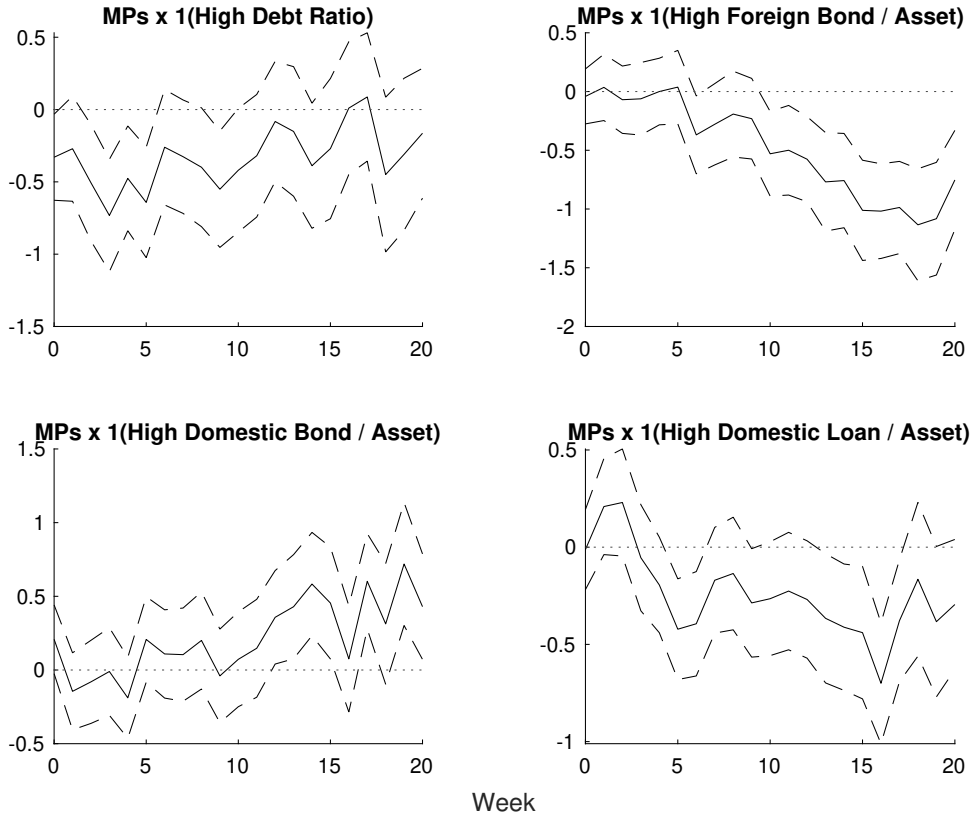


Figure 11: Response of NTL in Transacted Land to US MPs: RE Firm Debt and its Components

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors clustered to firm and week.

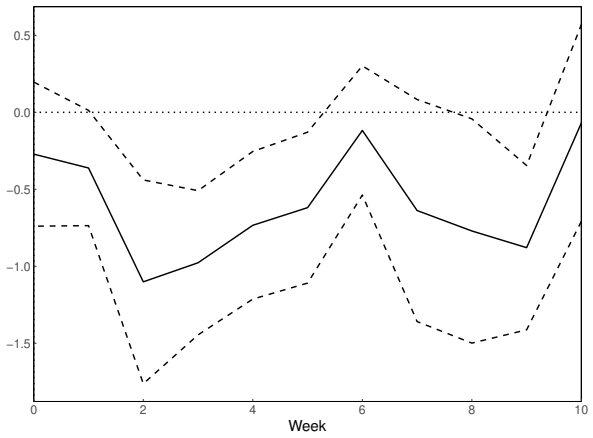


Figure 12: NTL Response to Interaction of US MPs and Bad Deal Index (Land Revenue-Weighted), City level

Notes: The dashed ribbons are the 90 percent confidence intervals generated based on standard errors clustered to city and week.

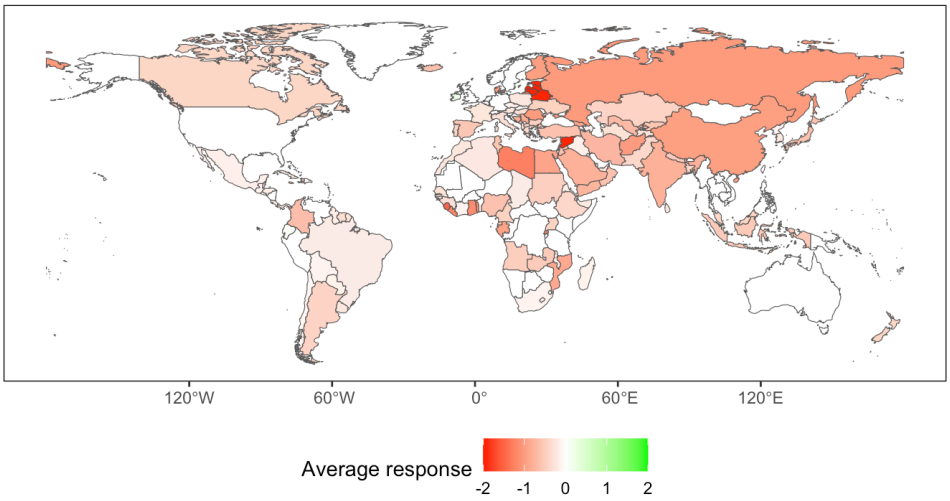


Figure 13: Average Response of NTL to US MPs by Economy

Notes: MPs is aggregated to the monthly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. When taking the average across the time horizon from the month the MPs is realized to 20 months later, insignificant values at a 90 percent confidence level are treated as zero. If the region has both significantly positive and significantly negative responses, the average response by the region is interpreted as zero. Extreme values with absolute values greater than 2 are winsorized on the map.

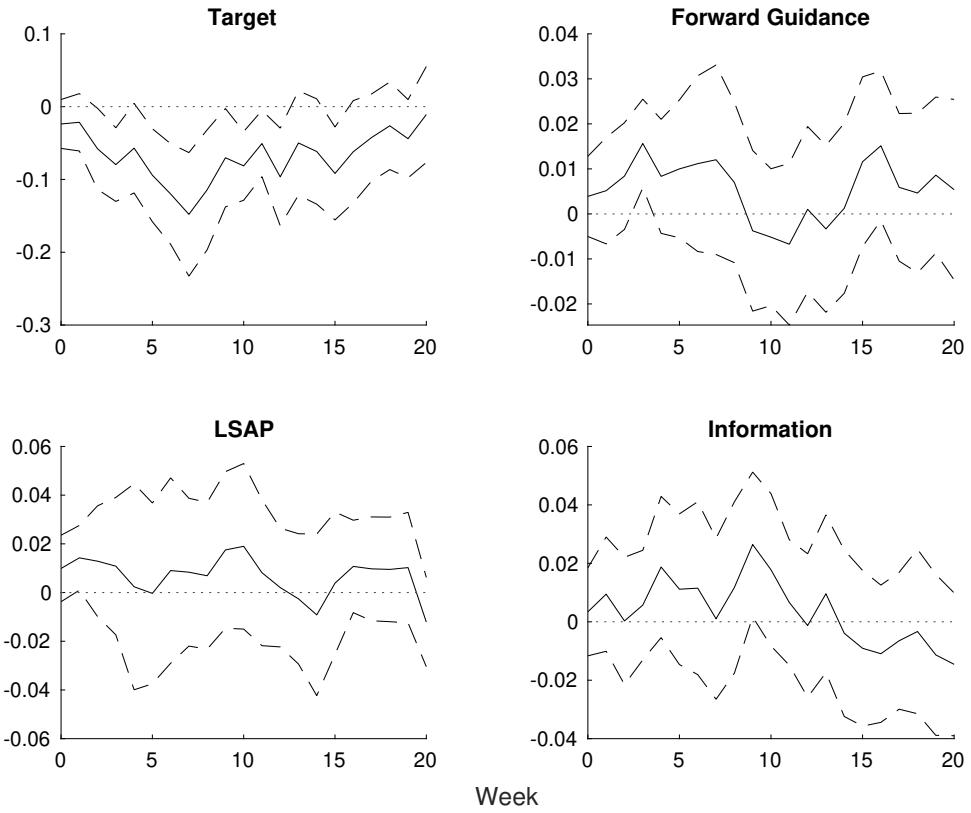


Figure 14: Local Projection of NTL on US MPs: Alternative Unconventional MPs

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

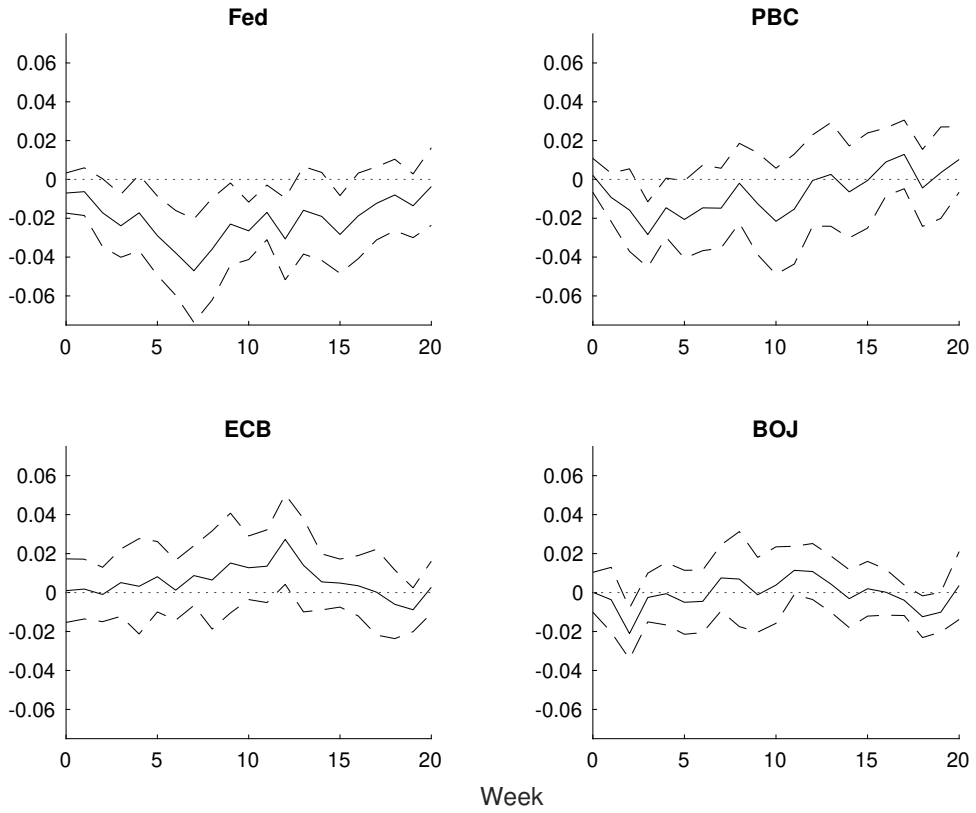


Figure 15: Local Projection of NTL on MPs by Different Central Banks

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. We normalize the standard deviation of all the shocks to be 1 for the full sample so that the impacts across the shocks are more comparable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

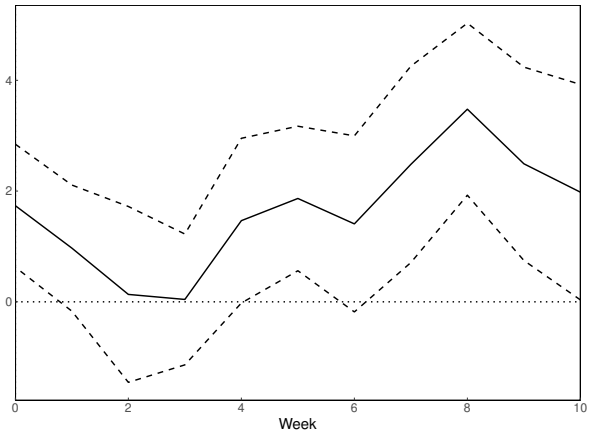


Figure 16: NTL Response to Interaction of US MPs and Trade Exposure, City level

Notes: The dashed ribbons are the 90 percent confidence intervals generated based on standard errors clustered to city and week.

Appendix A Data Appendix

A.1 Monetary policy shock

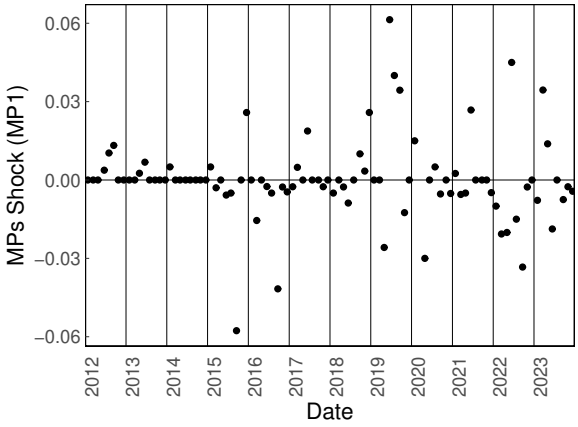


Figure A.1: Proxies of Monetary Policy Shock: Baseline

Notes: For each MPs event, the corresponding date is the day when the FOMC is held.

Table A.1: Summary Statistics: Monetary Policy Shock

	N	Mean	SD	Min	Max
Year	99	2017.61	3.49	2012.00	2024.00
Month	99	6.62	3.56	1.00	12.00
Day	99	17.95	9.36	1.00	31.00
MPs: MP1	95	0.0001	0.02	-0.06	0.06

Notes: The last day with non-zero baseline MPs: MP1 is on 2023-12-13. Only dates with MPs are included.

A.2 Details of NTL Data

A.2.1 Data Availability

Daily NTL The raw daily data are available on the official website of NASA at: https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/VNP46A2, and Google Earth Engine (GEE) at: https://developers.google.com/earth-engine/datasets/catalog/NOAA_VIIRS_001_VNP46A2. In this paper, the daily NTL data is derived from NASA's Black Marble product using the VIIRS instrument (NASA 2020). The product code of the stray light-corrected daily NTL series is VNP46A2. It corrects for stray light, such as wildfire and moonlight. It also adjusts for the satellite angle that varies each day when the satellite captures the image of the same place.

As an illustration, the map of NTL in the East Asia and Pacific region released by NASA in 2016 is as follows.[38]

[38]The original file is publicly available at:



Figure A.2: Nighttime Luminosity Captured by NASA Satellite in 2016

Monthly and Annual NTL The monthly NTL series has been available since April 2012. We use the stray-light corrected monthly series when studying the country-level NTL response to US MPs, as it is available globally without the necessity for post-processing.[39] The annual series has been available since 2012 (Elvidge et al., 2021).[40] This data is used to investigate the correlation between NTL and GDP across countries. The processed monthly and annual datasets are publicly available on the Earth Observation Group (EOG) website hosted by the Colorado School of Mines at: https://payneinstitute.mines.edu/eog/. EOG processes original satellite images to filter out ephemeral lights such as fire.

A.2.2 Daily NTL Data Processing

Raw Data Processing To smooth the cloud computing process on the Google Cloud Platform (GCP), we use the Google Earth Engine (GEE) repository to capture the daily NTL geospatial data. Firstly, we extract the map using a rectangle with longitudes from 75 to 135 degrees and latitudes from 18 to 53 degrees. The rectangle contains the whole land area of mainland China.[41] For each day's NTL data, we save four layers to the corresponding TIFF file: daily NTL (DNB_BRDF_Corrected_NTL), NASA-filled daily NTL (Gap_Filled_DNB_BRDF_ Corrected_NTL), quality flag (Mandatory_Quality_Flag), and snow flag (Snow_Flag). We do this for each day from 19 January 2012 to 31 December 2023 with 2,174 files.

https://www.nasa.gov/specials/blackmarble/media/BlackMarble20161km.jpg.

[39]The monthly series without stray-light correction is unavailable in summer in places with higher latitudes due to long daytime and even longer astronomical light in summer.

[40]The annual NTL data in 2012 is derived from April to December, while the annual data in forwarding years are all derived from corresponding monthly series from January to December in the same year. Before 2014, the summation is over the monthly series without stray-light correction. Since 2014, the derivation is based on the stray light-corrected monthly series.

[41]For Hainan province, we use another rectangle with longitudes from 108 to 112 degrees and latitudes from 17 to 21 degrees. We omit Sansha, a remote city with a small area far from the main body of Hainan Island.

NTL Series Construction (1) *Cell Series*: We filter out cells with contaminated daily NTL (e.g. by cloud or snow) and fill them with previous values. For each cell (defined by longitude and latitude), we keep the daily NTL value only if both the quality flag and the snow flag are zero, indicating no quality (e.g., cloud coverage) issue or snow-coverage issue in the cell. Then, we concatenate the dataset to a cell-level daily panel. For each cell, we obtain a time series with several missing values for the daily NTL. We fill the NA values with the latest valid value from the beginning to the end. Then, we fill the starting NA values using the earliest valid value, so the time series of each cell is fully filled. We call the filled daily NTL series the manually-filled NTL series. For each of the 4,332 available days, there are 55,404,633 cells for the whole country.

(2) *City Series*: Then, we concatenate the time series for each city, and the merged dataset is a city-level daily panel. The key variables in the panel include the city code and the date. For each city, we use the GIS (Geographic Information System) shape file.[42] We crop from the daily rectangles using the shape file. For the cropped dataset, we filter out observations without NASA-filled daily NTL (very few cases), as the value is supposed to be available for every legible cell on the map. The cropped dataset includes longitude, latitude, and the values of the four layers for each cell. For computational efficiency, we exclude cities with more than 500,000 cells. Consequently, we generate aggregated daily NTL series for 345 out of 367 cities (prefectures) in mainland China. For each city on each day, we record the number of valid cells and the sum of NTL. In the aggregated daily NTL series, we drop the dates where the valid cell numbers are less than 90 percent of the maximum cell number for either the NASA-filled NTL or the manually-filled NTL. Using the sum of NTL divided by the number of cells, we obtain the average NTL for each city on each day. The summary statistics of NTL in the weekly/city level are show in Table A.2.

Table A.2: Summary Statistics: Weekly NTL, City

	N	Mean	SD	Min	Max
Year	214793	2017.51	3.45	2012.00	2023.00
Month	214793	6.54	3.45	1.00	12.00
Day	214793	15.70	8.79	1.00	31.00
Sum of NTL	214793	86803.02	88277.75	382.97	1943628.94
Number of cell	214793	85543.86	85234.57	427.00	491798.00

Notes: The unit of NTL in each cell is average radiation (nW/cm2/sr). For each city, NTL are aggregated to week level by average. A week starts from Sunday.

(3) *National Series*: Finally, we also aggregate the city-level panel into a national-level daily NTL time series. For each day, we calculate the national average NTL weighted by the number of cells of each city.

[42]The shape files used to crop the GeoTiff files of NTL are from NewHorizon, a third-party provider of China's GIS information, most recently updated in 2022. They are based on the official shape files published by the National Bureau of Statistics of China (NBSC) with minor corrections to reflect the latest administrative division. Using the official shape files published by the NBSC in 2020 does not substantially change the results of the study.

Built-up Area We also apply the GIS shape file for the built-up area to crop from the daily rectangles. Similar to the city-level daily panel of NTL, we generate a city-level daily panel of NTL for each definition of built-up area: city center, suburb, and non-built-up area. The variables in the panel include the date, city code, city area, NTL, and the definition year of the built-up area (each five years from 1990 to 2015). Similarly, for each city area, we also aggregate it to a national weighted level time series.

Other Economies We apply the same method to crop regions in other economies, including Hong Kong (China), Macau (China), Taiwan (China), Mongolia, South Korea, Japan, Vietnam, Thailand, Bangladesh, India, and Australia. Like the balance we keep for computation power-saving and population coverage, we exclude some regions with relatively large area and small population. For Mongolia, we select 10 out of 21 regions, which represents over 70 percent of the national population. For Japan, we exclude Hokkaido. For Vietnam, we include the 25 out of 63 regions, which are in the northern part and represent about 40 percent of the national population. For India, we include 498 out of 676 secondary regions, excluding the southern, western, and Jammu and Kashmir regions. For Australia, we include Australian Capital Territory, Victoria, New South Wales, Queensland, and South Australia, which cover more than 80 percent of the national population.

Mountain Areas To remove mountain areas and other unhabitable areas in China, we use the land cover map from CLCD.[43] The geospatial map is derived from the Landsat satellite images on the Google Earth Engine. We use the version with 30 meter resolution identified for the year 2022. For each original cell, we identify it as inhabitable if it is not cropland or impervious, which consequently includes all forest, shrub, grassland, water, snow and ice, barren, and wetland cells. The cells are converted to 500-meter cells used in the NTL geospatial data. For each converted cell, we identify it as inhabitable if all associated original cells are inhabitable.

A.3 Land Transaction Data of China

China's land transaction data are processed from Land China (www.landchina.com).[44] Each land transaction is identified by an Electronic Identification number (EID). The sample period ranges from 2000 to 2020. For each land transaction, the dataset records the city, the address, the source of the land, the area, the financial amount of the transaction, the upper and lower bounds of the contracted floor-area ratio, the signing date of the contract, and the transacted party (usually a person or a firm).

To match each land transaction with a listed firm, we identify the best match from the name of the transacted party, searching for the name of the potential parent listed firm of the transacted party. For each transaction, we firstly try to directly match the transacted party with a listed firm according to the name of the transacted party. If we do not find a potential match, we manually expand the searching scope to subsidiaries of each listed firm, including those not directly identified from their names, using equity

[43]The tif file is publicly available at: https://zenodo.org/records/8176941.

[44]We thank Xiaoyu Zhang for sharing the processed data, including matching transactions to list firms and aggregating them to city level.

relationship in TianYanCha.[45] In this case, if the name of a transacted party matches a subsidiary firm, we match the transaction with the parent listed firm corresponding to the subsidiary firm. Currently, matches are available for all transactions from 2007 to 2015 and from 2017 to 2020. The summary statistics of the land transaction data are in Table A.3.

Table A.3: Summary Statistics: Land Transaction

	N	Mean	SD	Min	Max
Year	55090	2013.08	3.66	2007.00	2020.00
Month	55090	6.92	3.47	1.00	12.00
Day	55090	16.69	8.79	1.00	31.00
Area	55090	5.42	14.03	0.0003	1056.60
Revenue	55090	13166.19	48338.77	0.0001	3707364.00

Notes: The unit of area is hectare. The unit of revenue is 10,000 Yuan.

To aggregate the data to city level, we add the total area or revenue of all the transactions occurred within each city.

A.4 Bond issuance data

The confidential bond issuance data of Chinese firms are from Huang et al. (2024).[46] Each bond issuance is identified by an unique identification number. The sample period ranges from 2000 to 2015. For each bond issuance, the dataset records the issuer's name, the issuer's parent firm's name (if diffrent from the issuer), the matched listed firm (through stock market code), the firm's industry, the pricing date, the maturity date, the currency of the bond, and the value of the bond. It also provides information such as bond rating at issuance, current bond rating, whether the bond is of investment grade, yield to maturity, and the interest rate of the US and China on the bond pricing date.

We identify whether the issuance is domestic or foreign based on the currency of the bond. If the currency of the bond is Chinese Yuan (CNY), we classify the record as domestic. Otherwise, we classify it as foreign. In this study, we focus on the records matched to a listed real estate firm. For such records, 94.14 percent of the classified foreign issuance are denominated in US dollars (USD). Therefore, the US interest rate can be used as a good measure of the reference bond issuance rate. The summary statistics of the land transaction data are in Table A.4.

[45]Founded in October 2014, TianYanCha is a website under Beijing Jindi Technology Co., Ltd.. It allows users to search for various types of information about companies in mainland China.

[46]We thank Yi Huang for sharing the data.

Table A.4: Summary Statistics: Bond Issue

	N	Mean	SD	Min	Max
Pricing year	19354	2012.79	2.30	2000.00	2015.00
Pricing month	19354	6.67	3.33	1.00	12.00
Pricing day	19354	16.57	8.15	1.00	31.00
Maturing year	19354	2016.88	3.79	2003.00	2075.00
Maturing month	19354	6.59	3.35	1.00	12.00
Maturing day	19354	17.55	8.22	1.00	31.00
Total face value	19354	493.05	1791.02	0.08	161122.58

Notes: The unit of total face value is 1 million Yuan.

A.5 Other Data

A.5.1 Firm Data of China

The operation information of listed firms in China is from China Stock Market Accounting Research (CSMAR). It contains the quarterly financial reporting information of all listed firms in China's equity market from 2007 to 2023. Each listed firm is identified by the stock quote code. Key information we use includes the industry of the firm as classified by CSRC, balance sheet indicators (assets, liabilities, accounts receivable, accounts payable, pre-sale revenue, short-term loan, long-term loan, book value of illiquid liability maturing within one year, bond payable), earning indicators (revenue, profit) and cashflow indicators (cash balance at the beginning and the end of the period).

A.5.2 National Accounts

To associate variations in NTL with changes in economic activities, we need to obtain GDP and other national account indicators and adjust the NTL data to the same frequency. Two datasets are used for this purpose: the city-level annual panel in China and the country-level annual panel. We obtain the city-level national accounts of China from statistical yearbooks, which are published annually by the NBSC, and use data from 2012 to 2023. Indicators we use include total GDP, GDP in the primary, secondary, and tertiary sectors, import, and export.[47] Then, we get country-level national accounts from the World Development Indicator (WDI) of the World Bank and associate them with country-level NTL series from the Light pollution statistics. [48] We use data from 2012 to 2023 in line with the main panel.

A.5.3 Financial Data of China

We use China's financial market data, including interest rates, stock market indices, and exchange rates. They are at daily frequency, and we use full sample starting from 1990s. Interest rates we use include R007 (7-day interbank repo rate with collaterals) and SHIBOR (Shanghai Interbank Offering Rate). Stock market indices we use include SSE

[47]Import and export are available until 2021.

[48]The country-level NTL data here are from the Light pollution map, but they are derived from the same source as our main NTL series.

(Shanghai Stock Exchange) indices (Composite, Industrial, Real Estate, Infrastructure, Financial, SSE 180). Exchange rates we use include the exchange rate of USD to CNY.

A.5.4 Time Series Data of China at City Level

Most of the time series data we use are from CEIC, a comprehensive database for aggregated economic indicators. We use city-level indicators at annual frequency. We use the full sample starting from as early as 1990s. We also use some data from NBSC.

Annual series we use include urbanization indicators (urban constructed rate, urban area, urban area percentage, population urbanization percentage) and population From CEIC, we use real estate investment, land transaction data (transaction area and revenue), and floor space sold and waiting for sale.

A.5.5 Time Series Data of the US

Data of the US economy are from the FRED database provided by the Federal Reserve Bank (Fed) of St. Louis. We use industrial production data at monthly frequency (INDPRO).

Corresponding to the US MPs series, we also adopt the US news shocks (including shocks on GDP, CPI, PPI, employment, retail sales). A shock is the difference of realized and ex-ante expected values. The consensus expectations are available from the widely used survey by Action Economics, the successor to Money Market Services. We use the "advance" GDP release, headline CPI and PPI inflation, and non-farm payrolls from the employment report. The retail sales are the total sales including automobiles. This data is obtained from Lakdawala et al. (2021).

A.5.6 Weather

Like the NTL data, weather data are also available daily. Weather potentially impacts NTL through channels irrelevant to productivity. Therefore, we control for daily weather conditions as a robustness check. The weather series can also be used as a placebo test, as their changes are supposed to be relatively irrelevant to the MPs. The data source is the Global Surface Summary of the Day (GSOD) from the National Oceanic and Atmospheric Administration (NOAA).[49] We use the average daily temperature, visibility, and wind speed data since 2014 in the study.

Appendix B NTL and Output

In this section, we illustrate NTL is positively correlates with traditional economic activity indicators, such as GDP. Figure B.1 shows such associations at annual frequency and the city level.

[49]The data are publicly accessible at: https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00516.

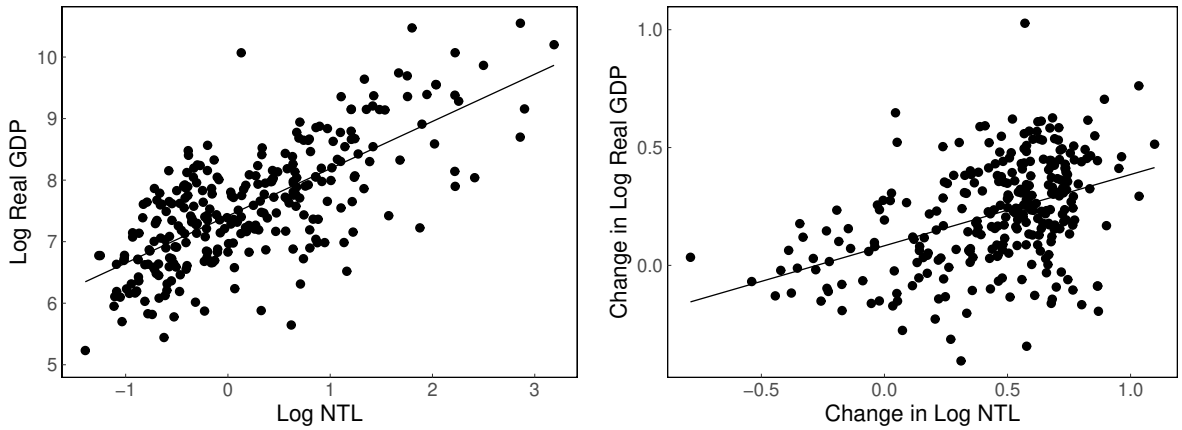


Figure B.1: NTL and GDP by City

Notes: Log NTL is converted to the corresponding frequency of the national account indicators in each plot. Log NTL is the logged value of the average NTL across every day in the converted periods. For each day, NTL is the average value of all cells in each city. The left graph shows the data in 2019. The right graph shows the changes from 2012 to 2019.

Using the annual panel data with NTL and different indicators from the national accounts, we apply the following regression equation.

$$y_{i,t} = \beta_0 l_{i,t} + \gamma_i + \tau_t + u_{i,t} \tag{B.1}$$

Here y is an output indicator (e.g., log GDP), and l is the log NTL. i and t are identifiers for city and year, respectively. We use NTL in the last year as the IV of the current NTL following J. Kim et al. (2022) and Chor and Li (2024). We also control for two-way fixed effects. When both y and l are in log forms, β_0 is the elasticity of output on NTL. The regression results of overall GDP and GDP by sector on NTL are in Table B.1.

The elasticity for aggregate GDP is about 0.49 (excluding Covid period), consistent with previous literature. Further looking at the elasticity by sector, the primary sector (agriculture) GDP does not correlate with NTL (Gibson et al., 2024), as agriculture activities mainly occur during the days. Both secondary (manufacturing and construction) and tertiary (service) sectors' GDP significantly and substantially correlate with NTL. Table B.2 implies the significant elasticity across periods. Therefore, the fluctuation in NTL reflects changes in economic output.

Next, we run the same regression in Equation B.1 at the country level using the cross-country national accounts, and the results are in Table B.3. In line with previous literature (Bickenbach et al., 2016; Henderson et al., 2012; Martínez, 2022), NTL has a higher correlation with GDP for emerging economies. Intuitively, several channels of GDP growth reflected on NTL mostly apply to emerging economies, including urbanization and night shifts in the manufacturing sector.

Table B.1: Regression of GDP on NTL: Sector

Dependent Variable:	Log GDP			
Sector:	All	Primary	Secondary	Tertiary
Model:	(1)	(2)	(3)	(4)
Variables (Second stage)				
Log NTL	0.4900***	0.1053	0.8280***	0.4938***
	(0.0793)	(0.0708)	(0.1254)	(0.0866)
Fixed-effects				
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
N	2,527	2,293	2,293	2,293
R^2	0.9873	0.9834	0.9676	0.9878
F-test	3,161.7	2,128.7	1,115.1	3,021.7

Notes: The COVID period from years 2020 to 2022 (both included) are excluded. The instrumental variable of the log nighttime light is the same indicator in the previous period. The first-stage regression coefficient is 0.6867 (s.e.: 0.0220). Significance levels are based on Clustered (Region) standard-errors. Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

Table B.2: Regression of GDP on NTL: Periods

Dependent Variable:	Log GDP			
Period:	All	Exclude COVID	2012-2016	2017-2023
Model:	(1)	(2)	(3)	(4)
Variables (Second stage)				
Log NTL	0.2559***	0.4900***	0.9435***	0.2802***
	(0.0583)	(0.0793)	(0.1124)	(0.0844)
Variables (First stage)				
Log NTL (Lag 1)	0.7234***	0.6867***	0.5188***	0.5060***
	(0.0135)	(0.0220)	(0.0317)	(0.0627)
Fixed-effects				
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
N	3,475	2,527	1,580	947
R^2	0.9861	0.9873	0.9936	0.9953
F-test	2,041.7	3,161.7	10,708.6	21,922.0

Notes: The COVID period includes years 2020 to 2022 (both included). The subperiod 2017 to 2023 also excludes the COVID period. Significance levels are based on Clustered (Region) standard-errors. Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

Table B.3: Regression of GDP on NTL: Countries by Income Group

Dependent Variable:	Log GDP		
Group:	All	Higher income	Lower income
Model:	(1)	(2)	(3)
Variables (Second stage)			
Log NTL	0.1420***	0.0403	0.1277**
	(0.0444)	(0.0717)	(0.0511)
Variables (First stage)			
Log NTL (Lag 1)	0.7791***	0.6812***	0.7687***
	(0.0407)	(0.0460)	(0.0588)
Fixed-effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
N	1,997	984	1,003
R^2	0.9990	0.9992	0.9986
F-test	19,166.4	11,904.7	7,313.8

Notes: The economies are classified into higher income and lower income economics by comparing their GDP per capita in 2012 with the median of all the economies in the sample. GDP value used is the constant GDP in 2015 US dollars (World Bank API indicator code: NY.GDP.MKTP.KD). Significance levels are based on Clustered (Region) standard-errors. Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

Appendix C More Results on Spillover Effects

Alternative Specifications and Measurements. (1) To exclude the noises from low-frequency factors, we add year-quarter fixed effects (FE) to our baseline specification. It does not substantially alter the short-term variation we intend to capture. (2) The response remains almost the same by replacing our baseline shock with the conventional MPs identified by Acosta (2022). (3) The confidence band is qualitatively the same by bootstrapping the standard error instead of using the Newey-West in the baseline. (4) We restrict the identification to exclude the lags of the shocks and use only one period lag of NTL change as a control; the results are quite close. (5) Concerning the measurement error induced by recorded light in the human-less areas, we remove the mountain and other uninhabitable areas and observe robust outcomes. These results are shown in Figure C.1.

Other confounding factors. There might be some confounding factors other than MPs that affect the NTL in China. (1) The NTL may also be affected by the US news shock that happened in the same week as the monetary announcement. So, we add some

concurrent macro news shocks (such as GDP, CPI, PPI, Employment, and Retail Sales) to the identification and find robust results, as shown in Figure C.2.[50] As another way to control the US macro news effect, we also add past cumulative news shocks to the baseline LP regression, and the result is qualitatively similar, see Figure C.3 (upper-left panel).[51] Besides, controlling US Industrial Production also yields a consistent conclusion, see Figure C.3 (upper-right panel). (3) The trade relationship between China and the US may determine China's real activities, thus we also try to control the US-China tension constructed by Rogers et al. (2024) in the baseline, and the results are almost unchanged. Refer to Figure C.3 (lower-left panel). (3) The NTL possibly changes with the weather conditions irrelevant to economic performance. To address this concern, we add weather controls to the baseline, and the results are robust and are displayed in Figure C.3 (lower-right panel). We also perform a falsification test by replacing the baseline's NTL with weather indicators. As expected, we do not find any significant responses by these indicators. The results are available upon request.

[50]The regression specification is the same as our baseline, and we control one news shock each time. The macro news shocks are the differences between the data release and the previous consensus expectations, which are obtained from the widely used survey by Action Economics, the successor to Money Market Services. We use the "advance" GDP release, headline CPI and PPI inflation, and non-farm payrolls from the employment report. The retail sales are the total sales including automobiles. The data are from Lakdawala et al. (2021).

[51]The regression specification is the same as our baseline, and we add past news as control variables. We use cumulative values for each macro news shock with a 60-day window before the FOMC meetings. Adjusting the window length does not qualitatively change the results. Here, we control all the news shocks simultaneously.

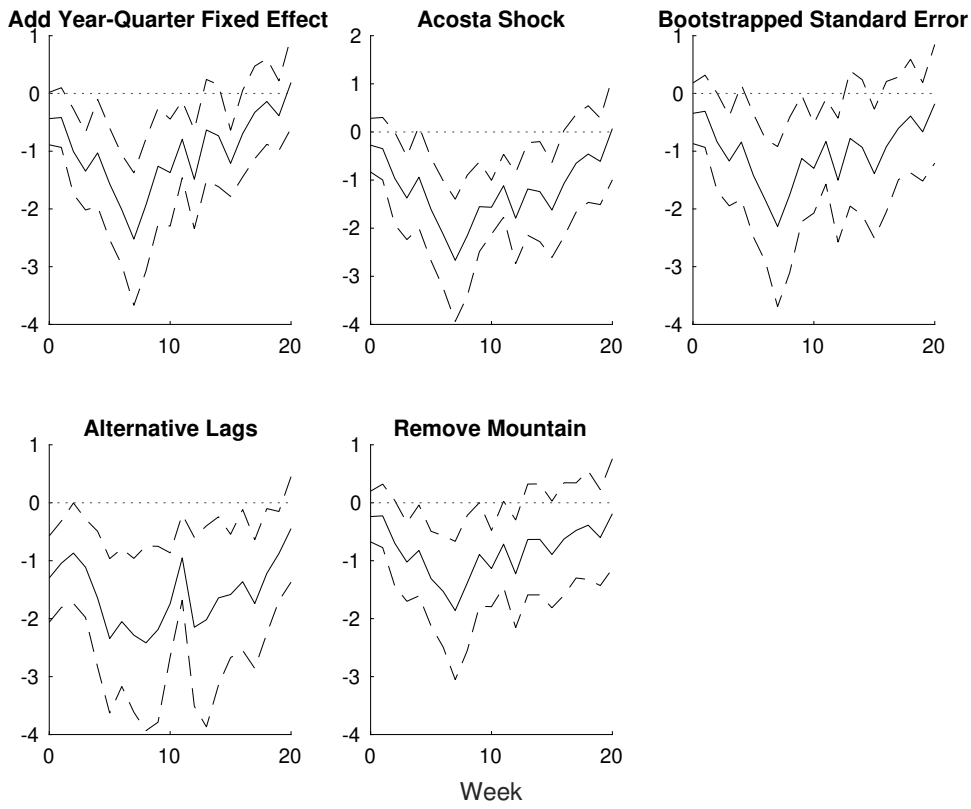


Figure C.1: Local Projection of China's NTL on US MPs: Alternative Measurements and Specifications

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

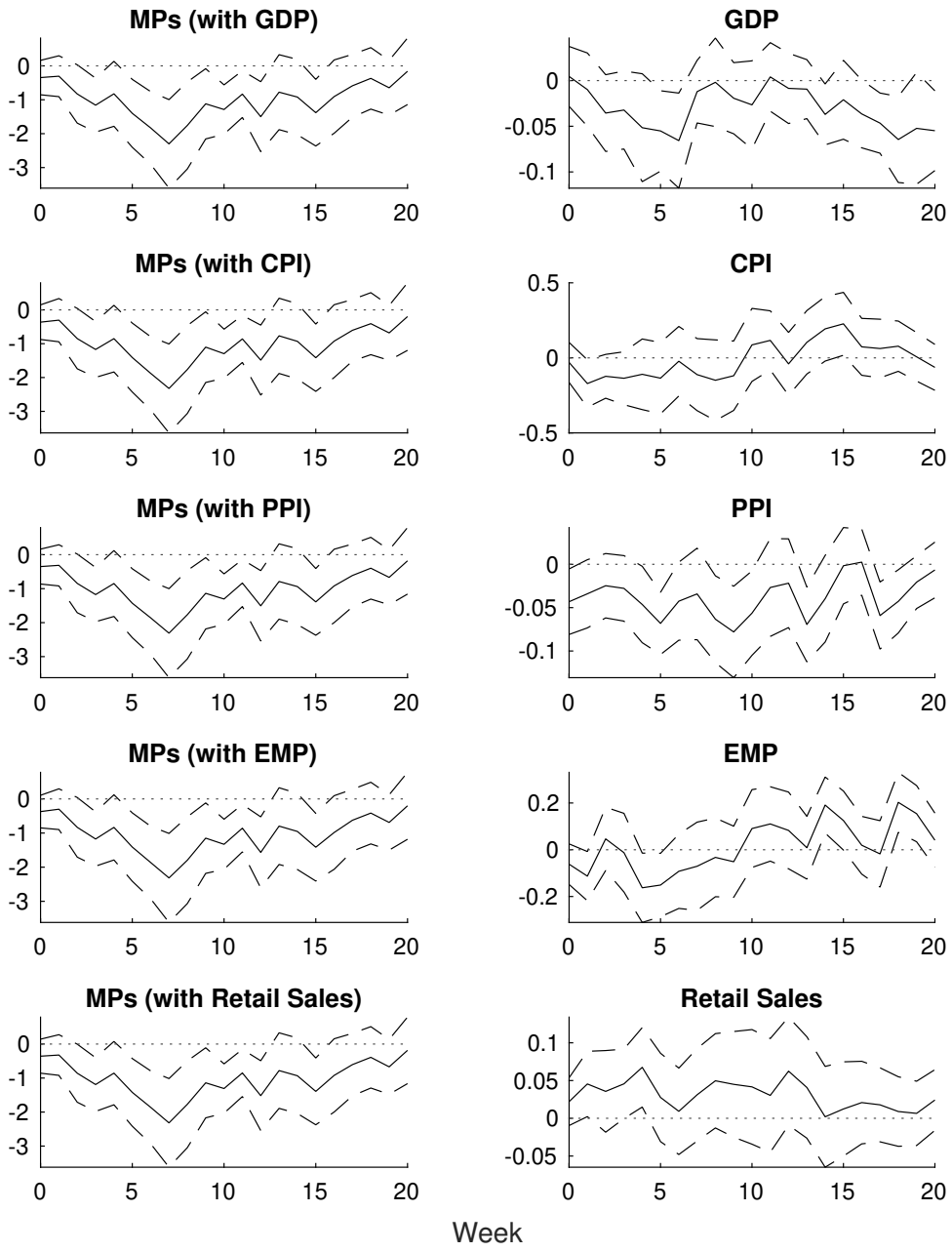


Figure C.2: Local Projection of NTL on US MPs and News Shock: News

Notes: Each row represents a LP regression, with the left column showing the NTL response to MPs, and the right column showing the NTL response to news shock. MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shocks (M_1 and M_2) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

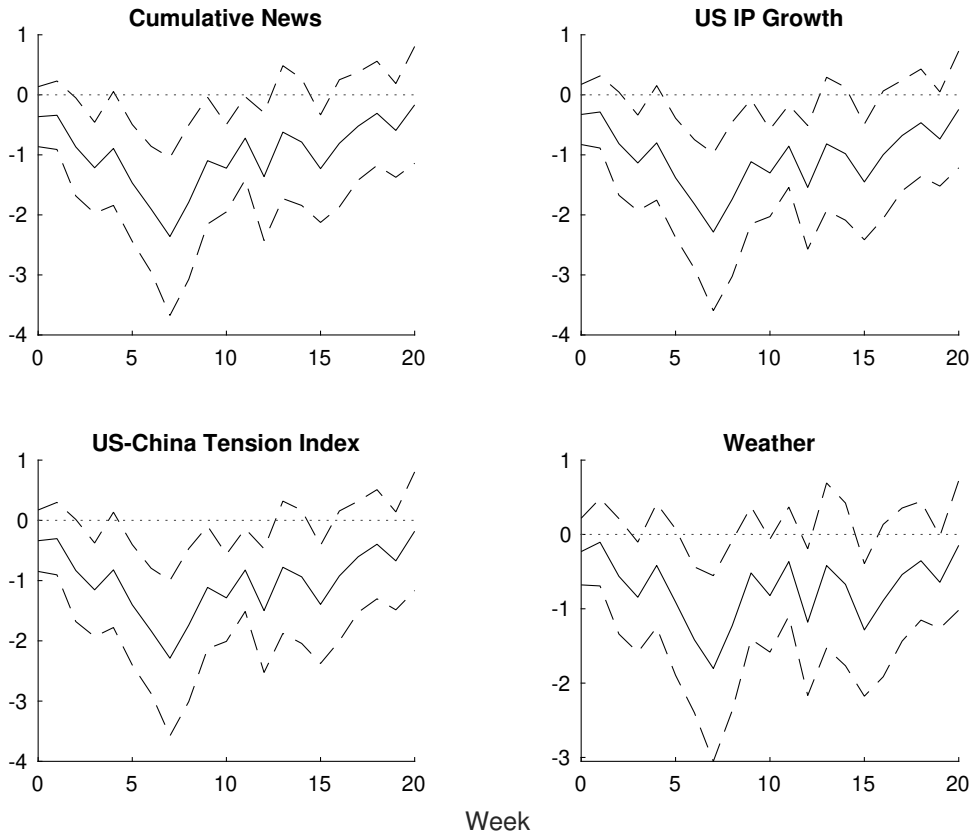


Figure C.3: Local Projection of NTL on US MPs: Adding Controls

Notes: For each graph, the title is the control added. For news, the control variables include cumulative GDP, CPI, PPI, employment, and retail sales news shocks. Each news shock is cumulative with a 60-day window before FOMC announcements. For US Industrial Production growth, Industrial Production is from a monthly series. Its values attached to each week are the period-to-period changes in the last period corresponding to the quarter and month of the week. For weather, control variables include average temperature, visibility, and wind speed. MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shocks (M_1 and M_2) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

Appendix D More Results on Channel

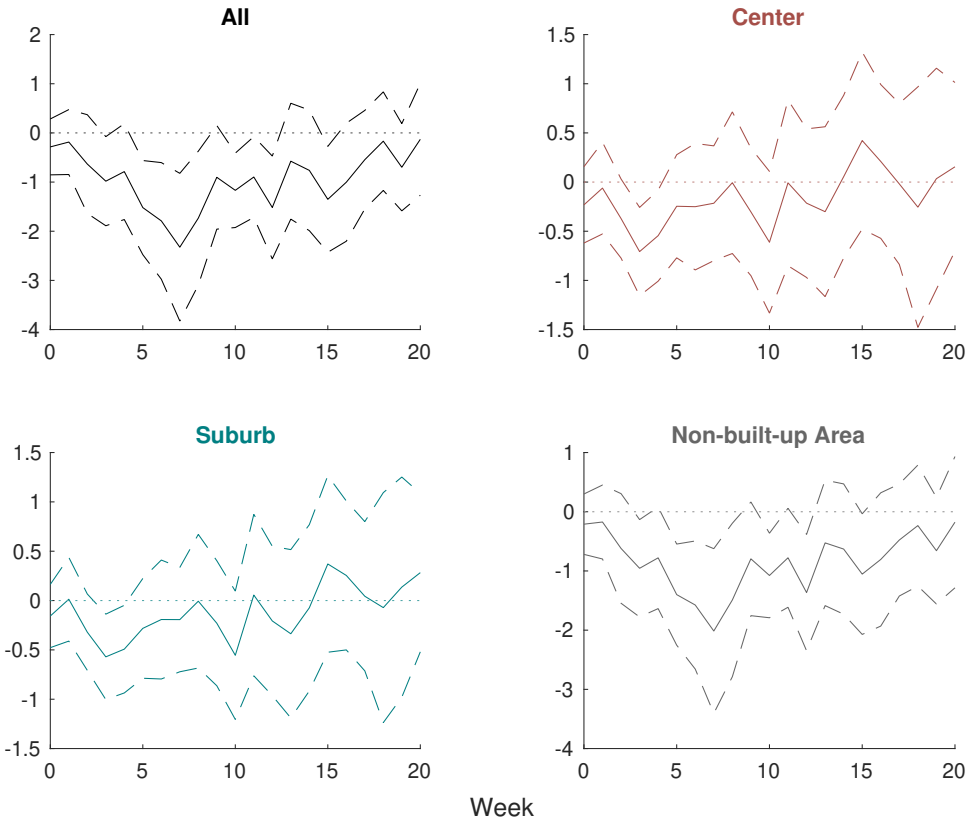


Figure D.1: Local Projection of NTL on US MPs: City Areas, Identified Built-up Area in 2015

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

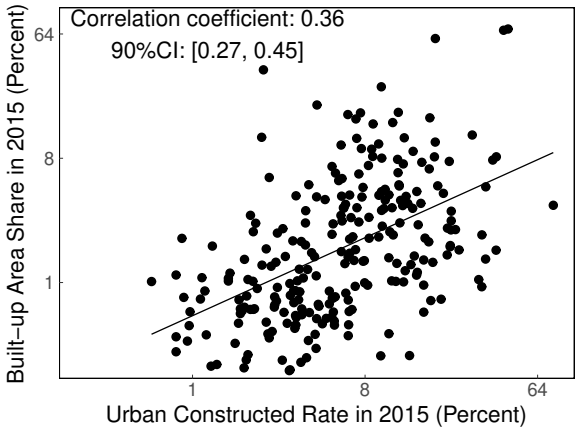


Figure D.2: Built-up Area Share and Urban Constructed Rate by City

Notes: For each city, the built-up area share is calculated as the ratio of the total number of NTL cells of the built-up area of the city over the total number of NTL cells of the city.

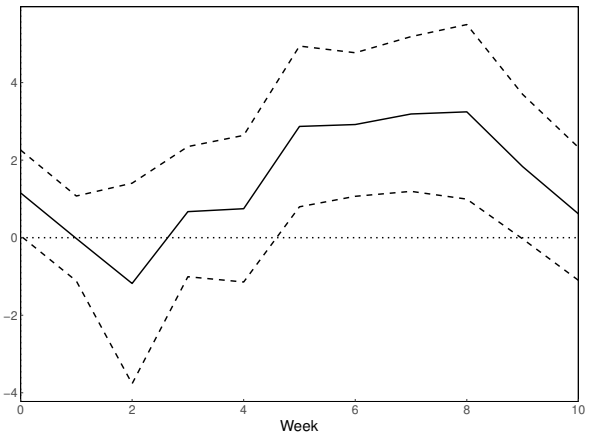


Figure D.3: NTL Response to Interaction of US MPs and Urban Area Rate, City level

Notes: The dashed ribbons are the 90 percent confidence intervals generated based on standard errors clustered to city and week.

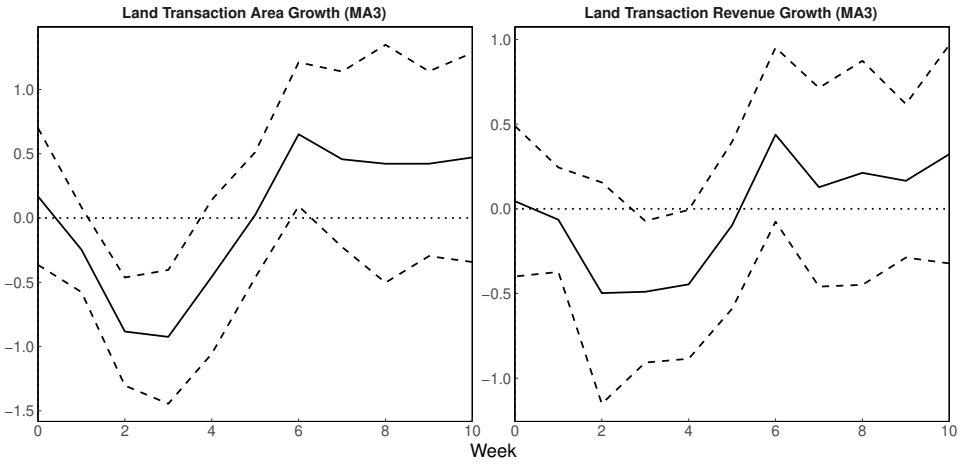


Figure D.4: NTL Response to Interaction of US MPs and Land Transaction, City level

Notes: For each city, the growth rate is calculated as the moving average of the annualized growth rates of aggregated values in the last three years (inclusive). The dashed ribbons are the 90 percent confidence intervals generated based on standard errors clustered to city and week.

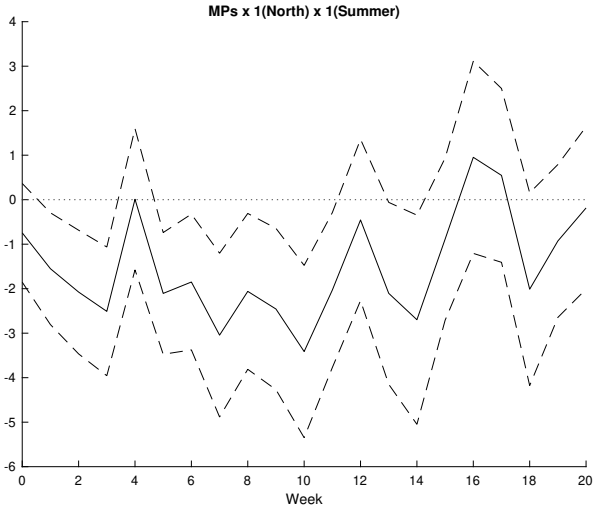


Figure D.5: Local Projection of NTL on US MPs: North and South, Summer versus Winter

Notes: MPs is aggregated to the weekly frequencies consistent with the dependent variable. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

Appendix E More Results on Financing Conditions

Table E.1: Real Estate Firm Foreign and Domestic Bond Issue Net Standing Value (Scaled by Operation Indicator) Responses to MPs

Panel A: Foreign Bond

	/ Asset	/ Liability	/ Current Liability	/ Long-term Liability
MPs	-0.0598***	-0.0801***	-0.1298***	-0.6261^{+}
	(0.0140)	(0.0199)	(0.0362)	(0.3868)
Firm FE	Yes	Yes	Yes	Yes
N	2,238	2,238	2,238	2,226
R^2	0.3390	0.3371	0.3616	0.1860

Panel B: Domestic Bond

	/ Asset	/ Liability	/ Current Liability	/ Long-term Liability
MPs	-0.0143	0.0891	0.0238	-1.9571
	(0.0819)	(0.2804)	(0.2952)	(1.6913)
Firm FE	Yes	Yes	Yes	Yes
N	3,955	3,955	3,955	3,862
R^2	0.4900	0.5744	0.5388	0.2400

Notes: Significance levels are based on Clustered (Firm) standard-errors. Significance Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.2.

Table E.2: Real Estate Firm Interest Expense (Scaled by Operation Indicator) Responses to MPs

	Interest Expense / Asset	Interest Expense / Liability	Interest Expense / Current Liability
MPs	3.1900***	3.7483***	2.9784***
	(0.7028)	(0.7870)	(0.7943)
Firm FE	Yes	Yes	Yes
N	4,832	4,832	4,831
R^2	0.8216	0.8175	0.8130

Notes: Significance levels are based on Clustered (Firm) standard-errors. Significance Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.2.

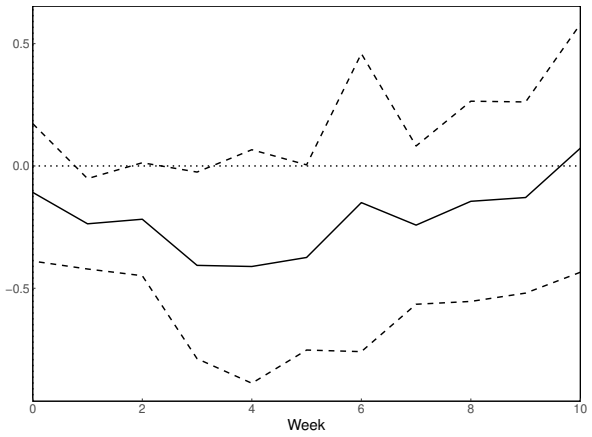


Figure E.1: NTL Response to Interaction of US MPs and Bad Deal Index (Land Area-Weighted), City level

Notes: The dashed ribbons are the 90 percent confidence intervals generated based on standard errors clustered to city and week.

Appendix F More Results on Further Discussion

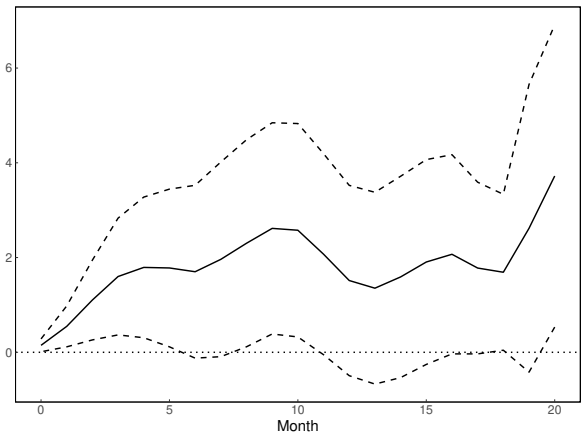


Figure F.1: NTL Response to Interaction of US MPs and Urbanization, Economy level

Notes: MPs is aggregated to the monthly frequencies consistent with the dependent variable. The dashed ribbons are the 90 percent confidence intervals generated based on standard errors clustered to economy and week.

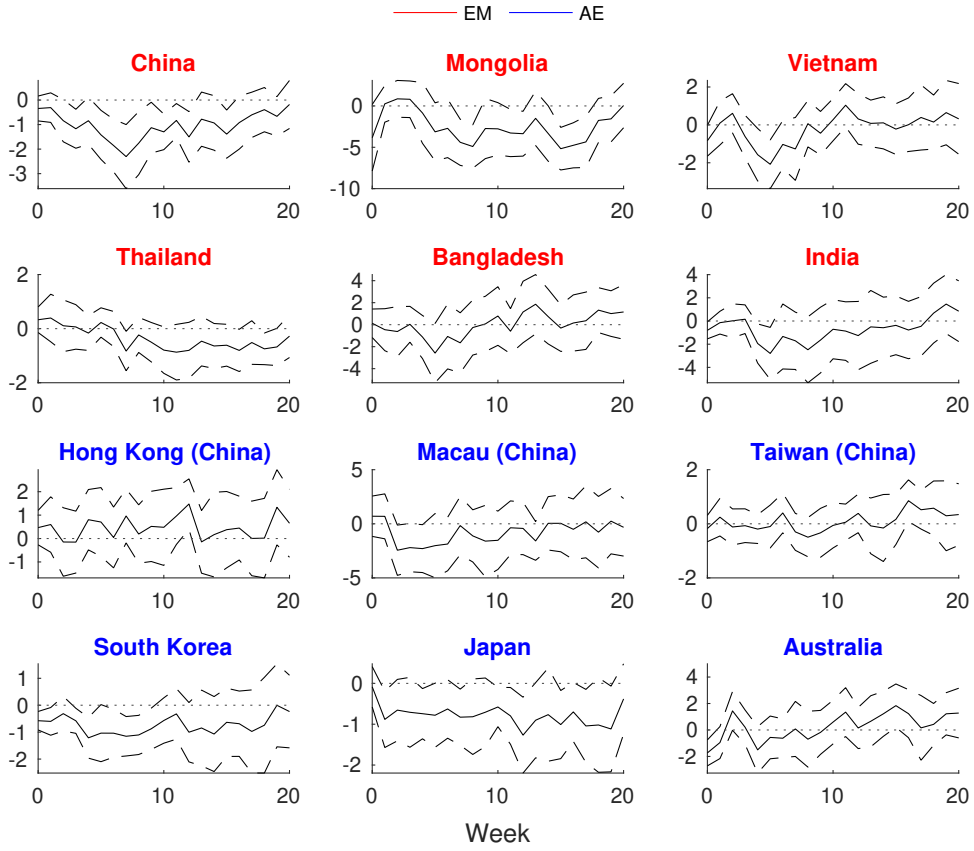


Figure F.2: Local Projection of NTL on US MPs: Other Economies

Notes: We apply the baseline specification on different economies respectively. MPs is aggregated to the weekly frequencies consistent with the dependent variable. The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.

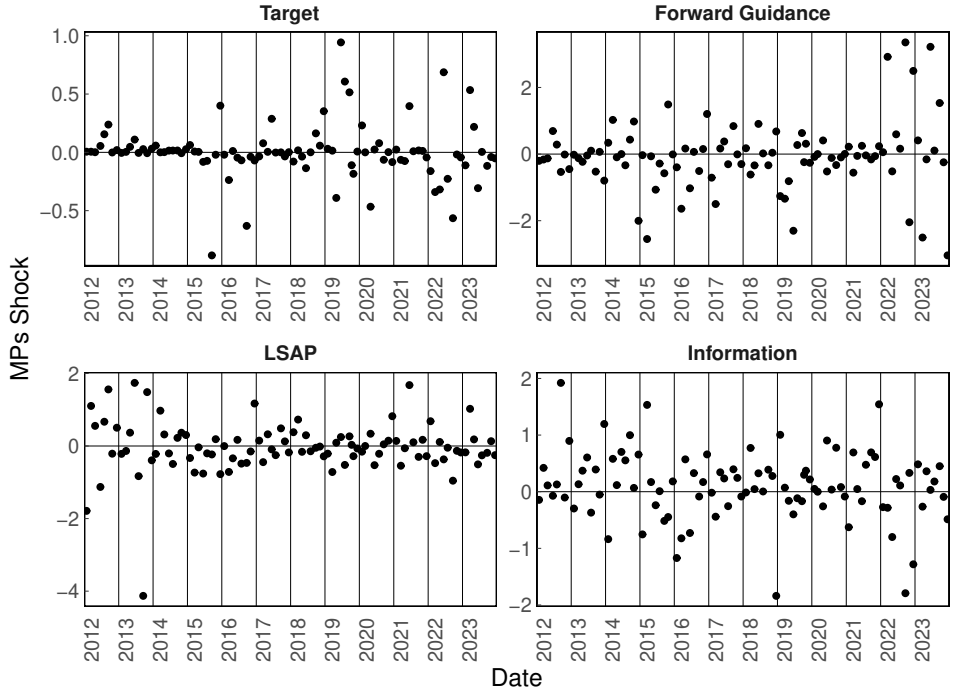


Figure F.3: Proxies of Monetary Policy Shock

Notes: For each MPs event, the corresponding date is the day when the FOMC is held.

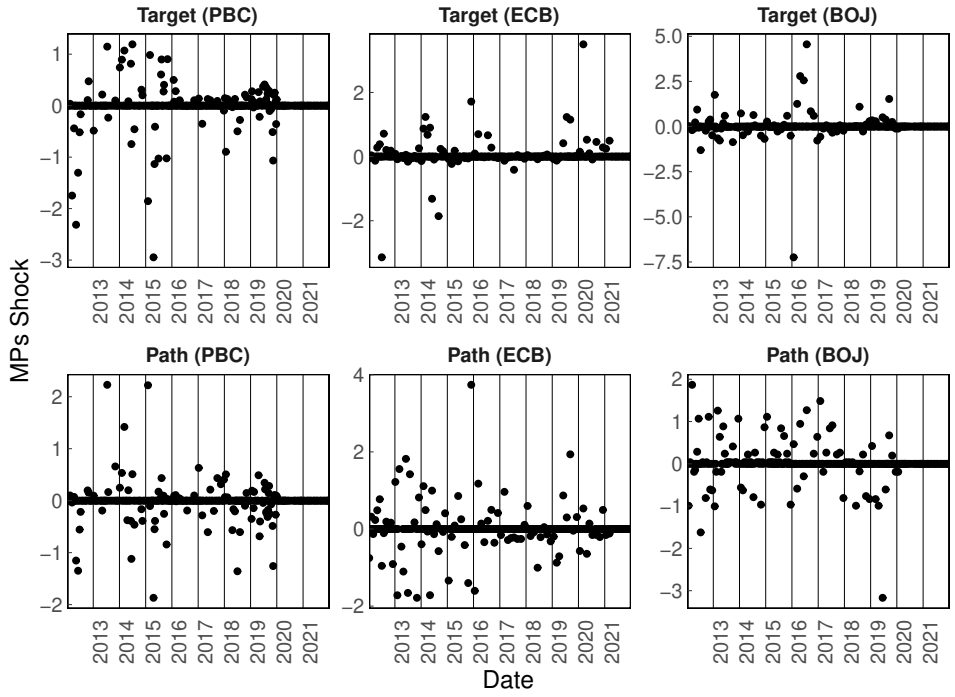


Figure F.4: Proxies of Monetary Policy Shock: Other Central Banks

Notes: For each MPs event, the corresponding date is the day when the FOMC is held.

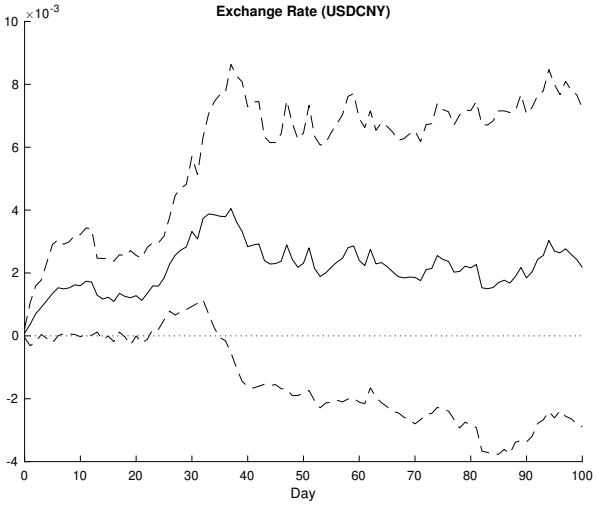


Figure F.5: Local Projection of Exchange Rate of USD/CNY to US MPs

Notes: The number of lags of the dependent variable (Q) and the shock (M) are selected by the AIC criteria for up to 4 periods. The dashed ribbons are the 90 percent confidence intervals generated based on the Newey-West standard errors.