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Mean Group Distributed Lag Estimation of Impulse Response Functions in Large Panels*

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Abstract

This paper develops Mean Group Distributed Lag (MGDL) estimation of impulse responses of common shocks in large panels with one or two cross-section dimensions. We derive sufficient conditions for asymptotic normality, and document satisfactory small sample performance using Monte Carlo experiments. Three empirical illustrations showcase the usefulness of MGDL estimators: crude oil price pass-through to U.S. city- and product-level retail prices; retail price effects of U.S. monetary policy shocks; and house price effects of U.S. monetary policy shocks.

Keywords: Large panels, impulse response functions, estimation and inference, mean group distributed lag approach (MGDL)

JEL Classification: C23, E52

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*The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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1 Introduction

The estimation of impulse-response functions (IRFs) has garnered growing interest in the recent literature. In the specific case when the shock of interest is assumed to be observed, it is now widely recognized that there exist numerous estimating equations within a time series framework that can be employed for estimating the impulse response function, either directly or through iterative methods. These include (i) the local projection (LP) regressions popularized by Jordà (2005), (ii) the distributed lag (DL) approach (e.g., Kimball et al. (2006), Kilian (2008a, 2009), Romer and Romer (2010), and Baumeister and Kilian (2014)), and (iii) iterative approaches utilizing autoregressive distributed lag (ARDL) regression specifications (e.g., Anzuini et al. (2013), Bachmeier and Cha (2011), Coibion (2012), Kimball et al. (2006), Romer and Romer (2004, 2010), Kilian (2008a, 2008b), among others) or the multivariate VAR or VARX specifications. Choi and Chudik (2019) investigated the relative merits of these approaches in finite samples of interest. However, extending these specifications to panel data setting is not straightforward, in part due to time series bias (as highlighted by Nickell (1981) in the context of dynamic panel data) and cross-sectional dependence. Mei, Sheng, and Shi (2023) considers the extension of local projections to panel setting.

This paper considers large panels with possibly two cross-section dimensions (motivated by our empirical illustrations), labeled as M and N, and a time dimension, T. It is assumed that the shock of interest is observed, common, and the impulse-responses follow a random coefficient specification. We allow for strong cross-section dependence and derive sufficient conditions for asymptotic normality of the Mean Group (MG) estimator based on augmented distributed lag specifications (hereafter, MGDL), assuming $(M, N, T) \to \infty$ jointly such that $N/T \to \kappa_1$ and $M/T \to \kappa_2$ for some $0 \leq \kappa_1, \kappa_2 < \infty$. This includes panels with cross-section and time dimensions that are large and of the same order, as well as panels with a time dimension that is large relative to the cross section dimension(s). In the former case, the usual nonparametric MG variance estimator, considered by Chudik and Pesaran (2019) for weakly correlated estimators, needs to be augmented due to the strong correlation of unit-specific estimators. We also present results for conventional panels with single cross-section dimension.

Monte Carlo experiments show satisfactory finite sample performance for the selected sample sizes of interest, $M = N \in \{30, 40, 50, 100\}$, and $T \geq 50$. We also investigate estimation of the cumulative sums of the impulse response function (also referred to as cumulative multipliers), including the possibility of direct estimation based on regressions with cumulated variables, $\xi_{ijt} = x_{ijt} + \xi_{i,j,t-1}$. Our results indicate that cumulative multipliers are more accurately estimated by cumulating estimated impulse response estimates rather than using regressions that involve cumulated variables.

Three empirical illustrations showcase the usefulness of the MGDL approach. The first illustration estimates the effects of crude oil price shocks, utilizing a quarterly retail price dataset at the city and product levels, complied by the Council for Community and Economic Research (C2ER, https://www.c2er.org/redt/). We find generic crude oil price increases are associated with a significant increase in retail gasoline prices. The estimated pass-through is fast and complete, in line with the existing crude oil pass-through literature. However, oil price shocks are generally not associated with significant effects on other product categories (with a single exception of the "shortening" category). The second illustration employes the same retail price dataset, but considers the effects of U.S. monetary policy shocks. Using five shock measures from the literature,[1] we find no significant effects of monetary policy shocks on city- and product-level retail prices. This surprising finding may stem from the fact that monetary policy shocks probably only contribute minimally to variations in retail prices. Additionally, these shocks are not accurately gauged, and the retail price data we have (specific to location and product) is prone to noise. The last illustration utilizes quarterly MSA-level house price dataset, where we find an unexpected but statistically significant positive effect of monetary policy shocks on house prices.

The remainder of the paper is organized as follows. Section 2 introduces the model, proposes the MGDL estimators, provides asymptotic results, and discusses potential extensions. Section 3 reports on evidence on the finite sample performance. Section 4 presents empirical illustrations. Section 5 concludes the paper. The mathematical derivations and proofs, and additional estimation results are provided in an appendix.

Throughout the paper, K and $K_0, K_1, ...$ indicate finite generic positive constants that depend neither on the sample size (M, N, T) nor on the subscripts (i, j, t). These constants could take different values at different instances in the paper. The symbols '$\to_p$' and '$\to_d$' respectively denote

[1] Bu, Rogers, and Wu (2021, BRW), Aruoba and Drechsel (2022, AD), Romer and Romer (2004, RR) updated by Wieland (2021), Nakamura and Steinsson (2018, NS), and Gürkaynak, Sack, and Swanson (2005, GSS).

the convergence in probability and distribution. '$\rightarrow_j$' denotes joint convergence. All vectors are column vectors, represented by bold lower case letters. Matrices are bold upper case letters. $\|\mathbf{A}\| = \sqrt{\varrho\left(\mathbf{A}'\mathbf{A}\right)}$ is the spectral norm of matrix $\mathbf{A}$,[2] $\varrho\left(\mathbf{A}\right) \equiv \max_{1\leq i\leq n} \{|\lambda_i\left(\mathbf{A}\right)|\}$ is the spectral radius of $\mathbf{A}$, and $|\lambda_1(\mathbf{A})| \geq |\lambda_2(\mathbf{A})| \geq ... \geq |\lambda_n(\mathbf{A})|$ are the eigenvalues of $\mathbf{A}$.

2 MGDL estimator

We consider a panel data with two cross-section dimensions (M, N) and a time dimension (T). Let x_{ijt} be a variable for the cross-section unit (i, j) in period t, observed for $i = 1, 2, ..., M$, $j = 1, 2, ..., N$, and $t = 1, 2, ..., T$. In the first two empirical illustrations developed in Section 4, the index i refers to individual price categories and the index j refers to geographic locations. We define the $M \times 1$ vectors $\mathbf{x}_{i\circ t} = (x_{i1t}, x_{i2t}, ..., x_{iMt})'$ and the $NM \times 1$ vector collecting all units as $\mathbf{x}_t = (\mathbf{x}'_{1\circ t}, \mathbf{x}'_{2\circ t}, ..., \mathbf{x}'_{N\circ t})'$. A special case of the single cross-section dimension, namely $M = 1$, is considered in Subsection 2.1.

Let v_t be a common shock observed for $t = 1, 2...., T$. We assume x_{ijt} can be decomposed as

$$x_{ijt} = a_{ij} + \sum_{\ell=0}^{\infty} b_{ij\ell} v_{t-\ell} + z_{ijt}, \tag{1}$$

where $b_{ij\ell}$ are the impulse-response coefficients of interest, v_t is uncorrrelated with $z_{ijt'}$, and the component z_{ijt} can be serially and cross-sectionally correlated. Decomposition (1) is quite general, and it would be implied, for instance, by a high-dimensional VAR data generating process for the $NM \times 1$ vector $\mathbf{x}_t$.

Let h be the chosen maximum horizon of interest that does not depend on the sample size (N, M, T). We collect $b_{ij\ell}$ for $\ell = 0, 1, ..., h$ into an $(h + 1) \times 1$ vector $\mathbf{b}_{ij} = (b_{ij0}, b_{ij1}, ..., b_{ijh})'$. The dependence of the dimension of $\mathbf{b}_{ij}$ on h is suppressed to simplify the notations. In addition, for chosen h, we assume that there possibly exists a $k_g \times 1$ vector $\mathbf{g}_{hijt}$ which is uncorrelated with $\{v_t, v_{t-1}, ..., v_{t-h}\}$, but can explain some of the variation in $\sum_{\ell=h+1}^{\infty} b_{ij\ell} v_{t-\ell} + z_{ijt}$. To this end, we

[2] Note that if $\mathbf{x}$ is a vector, then $\|\mathbf{x}\| = \sqrt{\varrho\left(\mathbf{x}'\mathbf{x}\right)} = \sqrt{\mathbf{x}'\mathbf{x}}$ corresponds to the Euclidean length of vector $\mathbf{x}$.

assume (1) can be written as

$$x_{ijt} = a_{ij} + \sum_{\ell=0}^{h} b_{ij\ell} v_{t-\ell} + \boldsymbol{\varphi}'_{hij} \mathbf{g}_{hijt} + e_{hijt}, \tag{2}$$

and postulate the following assumptions on the impulse-response coefficients $\mathbf{b}_{ij}$, the shock v_t, and the high-level requirements on $\mathbf{g}_{hijt}$ and e_{hijt}.

ASSUMPTION 1 *(Random coefficient assumption)* $\mathbf{b}_{ij} = \mathbf{b}_i + \mathbf{c}_j + \boldsymbol{\omega}_{ij}$, *where* $\mathbf{b}_i$ *and* $\mathbf{c}_j$ *are non-random and* $\boldsymbol{\omega}_{ij} \sim IID\left(\mathbf{0}, \boldsymbol{\Omega}_{ij}\right)$. *Furthermore,* $\sum_{j=1}^{N} \mathbf{c}_j = \mathbf{0}$, *and there exist constants* K, K_0, K_1 *and* $0 \leq \rho < 1$ *such that* $\|\mathbf{b}_i\| < K$, $\|\mathbf{c}_j\| < K$, *and* $K_0 < \|\boldsymbol{\Omega}_{ij}\| < K_1$.

ASSUMPTION 2 *(Shock v_t)* v_t *is independent of* $v_{t'}$ *for any* $t \neq t'$. *In addition,* $E\left(v_t^2\right) = \sigma_v^2$ *and there exist constants* K_0, K_1 *such that* $K_0 < E\left(v_t^4\right) < K_1$.

ASSUMPTION 3 *(High-level conditions on $\mathbf{g}_{hijt}$ and e_{hijt}). Let* $\bar{e}_{hi\circ t} = N^{-1} \sum_{j=1}^{N} e_{hijt}$, $\bar{e}_{h\circ jt} = M^{-1} \sum_{i=1}^{M} e_{hijt}$, $\bar{e}_{h\circ\circ t} = M^{-1} N^{-1} \sum_{i=1}^{M} \sum_{j=1}^{N} e_{hijt}$, *and* $\mathbf{M}_{hij} = \mathbf{I}_{T-h} - \tilde{\mathbf{G}}_{hij} \left(\tilde{\mathbf{G}}'_{hij} \tilde{\mathbf{G}}_{hij}\right)^{-1} \tilde{\mathbf{G}}'_{hij}$, *where* $\tilde{\mathbf{G}}_{hij} = \left(\boldsymbol{\tau}_{T-h}, \mathbf{G}_{hij}\right)$, $\boldsymbol{\tau}_{T-h}$ *is a* $T-h \times 1$ *vector of ones and* $\mathbf{G}_{hij} = \left(\mathbf{g}_{hij,h+1}, \mathbf{g}_{hij,h+2}, ..., \mathbf{g}_{hij,T}\right)'$. *When* $M, N, T \rightarrow_j \infty$ *such that* $M/T \rightarrow \kappa_1$ *and* $N/T \rightarrow \kappa_2$, *for some* $0 \leq \kappa_1, \kappa_2 < \infty$, *we have*

i) $\frac{\mathbf{V}' \mathbf{M}_{hij} \mathbf{V}}{T-h} \rightarrow_p \sigma_v^2 \mathbf{I}_{h+1}$,

ii) $\frac{\mathbf{V}' \mathbf{M}_{hij} \bar{\mathbf{e}}_{hi\circ}}{\sqrt{T-h}} \rightarrow_d N\left(0, \sigma_v^2 \varkappa_{hi} \mathbf{I}_{h+1}\right)$, *for some* $\varkappa_{hi} < \infty$, *and*

iii) $\frac{\mathbf{V}' \mathbf{M}_{hij} \left(\bar{\mathbf{e}}_{h\circ j} - \bar{\mathbf{e}}_{h\circ\circ}\right)}{\sqrt{T-h}} \rightarrow_d N\left(0, \sigma_v^2 \pi_{hj} \mathbf{I}_{h+1}\right)$, *for some* $\pi_{hj} < \infty$.

The object of interest is the estimation of parameter vectors $\mathbf{b}_i$ and $\mathbf{c}_j$ in Assumption 1. Assumptions 1-3 are not much restrictive. As mentioned earlier, $\mathbf{x}_t$ could be given by a high-dimensional VAR model. Alternatively, $\mathbf{x}_t$ can be represented by a high-dimensional MA(∞) process that falls outside VAR representations. In addition, unobserved common shocks (other than v_t) or unobserved factors are accommodated by Assumption 3.ii and iii. Our high-level assumptions are also compatible with heteroskedasticity of the unobserved component e_{hijt} in all dimensions.

This paper considers a mean group approach built on the unit-specific augmented DL regressions given by (2). One possible choice for variables in $\mathbf{g}_{hijt}$ is the appropriately lagged dependent variable, namely $x_{ij,t-h-s}$ for $s > 0$. Deterministic variables (such as seasonal dummies) or any other variables assumed to be uncorrelated with $\{v_t, v_{t-1}, ..., v_{t-h}\}$ could be included as well. It is not necessary to include variables in $\mathbf{g}_{hijt}$ for consistent estimation, namely $\mathbf{g}_{hijt}$ could be an empty vector.

One maintained assumption of this setup is that v_t is observed, which may restricts the applicability of this approach.

Let $\hat{b}_{ij\ell}$ denote the corresponding LS estimates of $b_{ij\ell}$ using (2), which we collect in an $(h+1)\times 1$ vector $\hat{\mathbf{b}}_{ij} = \left(\hat{b}_{ij0}, \hat{b}_{ij1}, ..., \hat{b}_{ijh}\right)'$. The Mean Group Distributed Lag (MGDL) estimators of $\mathbf{b}_i$ and $\mathbf{c}_j$, respectively, are given by

$$\hat{\mathbf{b}}_i = N^{-1}\sum_{j=1}^{N} \hat{\mathbf{b}}_{ij}, \text{ for } i = 1, 2, ..., M, \tag{3}$$

and

$$\hat{\mathbf{c}}_j = M^{-1}\sum_{i=1}^{M} \left(\hat{\mathbf{b}}_{ij} - \hat{\mathbf{b}}_i\right), \text{ for } j = 1, 2, ..., N. \tag{4}$$

The following theorem establishes sufficient conditions for asymptotic normality of the MGDL estimators.

Theorem 1 *(Consistency) Let x_{ijt} be given by (2) and Assumptions 1-3 hold. Consider $\hat{\mathbf{b}}_i$ and $\hat{\mathbf{c}}_j$ given by (3) and (4), respectively. Let $h \geq 0$ be a fixed integer that does not depend on the sample size (M, N, T), and suppose $M, N, T \rightarrow_j \infty$ such that $M/T \rightarrow 0$ and $N/T \rightarrow 0$, then we have*

$$\sqrt{N}\left(\hat{\mathbf{b}}_i - \mathbf{b}_i\right) \rightarrow_d N\left(0, \bar{\mathbf{\Omega}}_{i\circ}\right), \text{ and } \sqrt{M}\left(\hat{\mathbf{c}}_j - \mathbf{c}_j\right) \rightarrow_d N\left(0, \bar{\mathbf{\Omega}}_{\circ j}\right), \tag{5}$$

where $\bar{\mathbf{\Omega}}_{i\circ} = N^{-1}\sum_{j=1}^{N} \mathbf{\Omega}_{ij}$, and $\bar{\mathbf{\Omega}}_{\circ j} = M^{-1}\sum_{i=1}^{M} \mathbf{\Omega}_{ij}$.

If $M, N, T \rightarrow_j \infty$ such that $M/T \rightarrow \kappa_1$ and $N/T \rightarrow \kappa_2$, for some $0 < \kappa_1, \kappa_2 < \infty$, then

$$\sqrt{N}\left(\hat{\mathbf{b}}_i - \mathbf{b}_i\right) \rightarrow_d N\left(\mathbf{0}, \mathbf{\Psi}_{1,i}\right), \text{ and } \sqrt{M}\left(\hat{\mathbf{c}}_j - \mathbf{c}_j\right) \rightarrow_d N\left(\mathbf{0}, \mathbf{\Psi}_{2,j}\right), \tag{6}$$

where $\mathbf{\Psi}_{1,i} = \bar{\mathbf{\Omega}}_{i\circ} + \kappa_1 \mathbf{\Upsilon}_{1,i}$, $\mathbf{\Psi}_{2,j} = \bar{\mathbf{\Omega}}_{\circ j} + \kappa_2 \mathbf{\Upsilon}_{2,j}$, and $\mathbf{\Upsilon}_{1,i}, \mathbf{\Upsilon}_{2,j}$ are defined in (A.3) and (A.4) in the Appendix.

Proofs are presented in the Appendix.

For asymptotic distribution to depend only on $\mathbf{\Omega}_{ij}$, we require $N/T \to 0$ (for $\hat{\mathbf{b}}_i$) and $M/T \to 0$ (for $\hat{\mathbf{c}}_j$). When $M/T \to \kappa_1 > 0$ and $N/T \to \kappa_2 > 0$ as $M, N, T \to_j \infty$, then the asymptotic variance in general depends on additional terms, arising from the strong cross section dependence of e_{hijt}, which can arise when $b_{ij\ell}$ are nonzero for $\ell > h$, and/or from the presence of additional common shocks and/or unobserved common factors.

To conduct inference, $\bar{\mathbf{\Omega}}_{i\circ}$ and $\bar{\mathbf{\Omega}}_{\circ j}$ can be estimated using

$$\hat{\mathbf{\Omega}}_{i\circ} = \frac{1}{N(N-1)} \sum_{j=1}^{N} \hat{\boldsymbol{\omega}}_{ij} \hat{\boldsymbol{\omega}}'_{ij}, \tag{7}$$

and

$$\hat{\mathbf{\Omega}}_{\circ j} = \frac{1}{M(M-1)} \sum_{i=1}^{M} \hat{\boldsymbol{\omega}}_{ij} \hat{\boldsymbol{\omega}}'_{ij}, \tag{8}$$

where $\hat{\boldsymbol{\omega}}_{ij} = \hat{\mathbf{b}}_{ij} - \hat{\mathbf{b}}_i - \hat{\mathbf{c}}_j$. Hence, the standard non-parametric variance estimators for mean group estimation are valid when $N/T \to 0$ (for $\hat{\mathbf{b}}_i$) and $M/T \to 0$ (for $\hat{\mathbf{c}}_j$). However, in the case when the cross-section and time dimensions are of the same order, then the usual nonparametric mean group estimators would no longer suffice due to the additional terms in $\mathbf{\Psi}_{1,i}$ and $\mathbf{\Psi}_{2,j}$, see (6). $\mathbf{\Psi}_{1,i}$ and $\mathbf{\Psi}_{2,j}$ can be estimated as

$$\hat{\mathbf{\Psi}}_{1,i} = \hat{\mathbf{\Omega}}_{i\circ} + \frac{M}{T} \hat{\mathbf{\Upsilon}}_{1,i} \tag{9}$$

and

$$\hat{\mathbf{\Psi}}_{2,j} = \hat{\mathbf{\Omega}}_{\circ j} + \frac{N}{T} \hat{\mathbf{\Upsilon}}_{2,j}, \tag{10}$$

respectively, where $\hat{\mathbf{\Upsilon}}_{1,i} = \hat{\sigma}_v^{-2} \hat{\varkappa}_{hi} \mathbf{I}_{h+1}$, $\hat{\mathbf{\Upsilon}}_{2,j} = \sigma_v^{-2} \hat{\omega}_{hj} \mathbf{I}_{h+1}$, $\hat{\sigma}_v^2 = (T-h)^{-1} \sum_{t=h+1}^{T} v_t^2$, $\hat{\varkappa}_{hi} = (T-h) \sum_{t=h+1}^{T} \widehat{\bar{e}}_{hi\circ t}^2$, $\hat{\omega}_{hj} = (T-h)^{-1} \sum_{t=h+1}^{T} \left(\widehat{\bar{e}}_{h\circ jt} - \widehat{\bar{e}}_{h\circ\circ t}\right)^2$, and $\left\{\widehat{\bar{e}}_{hi\circ t}^2, \widehat{\bar{e}}_{h\circ jt}, \widehat{\bar{e}}_{h\circ\circ t}\right\}$ are computed using the residuals from (2), denoted as $\hat{e}_{hijt}$.

2.1 MGDL estimator in large panels with a single cross section dimension

Suppose $M = 1$. Hence, we have data (dropping subscript $i = 1$) on x_{jt}, generated according to

$$x_{jt} = a_j + \sum_{\ell=0}^{h} b_{j\ell} v_{t-\ell} + \boldsymbol{\varphi}'_{hj} \mathbf{g}_{hjt} + e_{hit}. \tag{11}$$

In this setting, we replace the random coefficient Assumption 1 with the following assumption on the elements of $\mathbf{b}_j = (b_{j0}, b_{j1}, ..., b_{jh})'$.

ASSUMPTION 4 *(Random coefficient assumption for a single cross-section dimension)* $\mathbf{b}_j = \mathbf{b} + \boldsymbol{\omega}_j$*, where* $\boldsymbol{\omega}_j \sim IID\,(\mathbf{0}, \boldsymbol{\Omega})$*. Furthermore, there exist constants* K_0 *and* K_1*such that* $\|\mathbf{b}\| < K$*, and* $K_0 < \|\boldsymbol{\Omega}\| < K_1$*.*

The following assumption replaces Assumptions 3 for the case of a single-cross-section dimension.

ASSUMPTION 5 *Let* $\bar{e}_{h\circ t} = N^{-1} \sum_{j=1}^{N} e_{hjt}$ *and* $\mathbf{M}_{hj} = \mathbf{I}_{T-h} - \tilde{\mathbf{G}}_{hj} \left(\tilde{\mathbf{G}}'_{hj} \tilde{\mathbf{G}}_{hj} \right)^{-1} \tilde{\mathbf{G}}'_{hj}$*, where* $\tilde{\mathbf{G}}_{hj} = (\boldsymbol{\tau}_{T-h}, \mathbf{G}_{hj})$*,* $\boldsymbol{\tau}_{T-h}$ *is* $T - h \times 1$ *vector of ones and* $\mathbf{G}_{hj} = (\mathbf{g}_{hj,h+1}, \mathbf{g}_{hj,h+2}, ..., \mathbf{g}_{hj,T})'$*. If* $N, T \to_j \infty$ *such that* $N/T \to \kappa$*, for some* $0 \leq \kappa < \infty$*, then:*

i) $\frac{\mathbf{V}'\mathbf{M}_{hj}\mathbf{V}}{T-h} \to_p \sigma_v^2 \mathbf{I}_{h+1}$*, and*

ii) $\frac{\mathbf{V}'\mathbf{M}_{hj}\bar{\mathbf{e}}_{h\circ}}{\sqrt{T-h}} \to_d N\left(0, \sigma_v^2 \varkappa_h \mathbf{I}_{h+1}\right)$*, for some* $\varkappa_h < \infty$*.*

The following proposition establishes asymptotic normality of the MGDL estimator. The asymptotic analysis is similar in the case of single-cross-section panels.

Proposition 1 *Let* $M = 1$*, and (dropping the subscript* $i = 1$*) suppose* x_{jt} *is generated by (11), let Assumptions 2 and 4-5 hold, and let* $h \geq 0$ *be a fixed integer that does not depend on the sample size* (N, T)*. Consider the MGDL estimator*

$$\hat{\mathbf{b}} = N^{-1} \sum_{j=1}^{N} \hat{\mathbf{b}}_j, \tag{12}$$

where $\hat{\mathbf{b}}_j$ *is the unit-specific LS estimator of* $\mathbf{b}_j$ *using the regression (11).*

(i) Suppose $N, T \to_j \infty$ such that $N/T \to 0$, then,

$$\sqrt{N}\left(\hat{\mathbf{b}} - \mathbf{b}\right) \to_d N\left(\mathbf{0}, \mathbf{\Omega}\right). \tag{13}$$

(ii) Suppose $N, T \to_j \infty$ such that $N/T \to \kappa$, for some $0 < \kappa < \infty$. Then

$$\sqrt{N}\left(\hat{\mathbf{b}} - \mathbf{b}\right) \to_d N\left(\mathbf{0}, \mathbf{\Omega} + \kappa\mathbf{\Upsilon}\right), \tag{14}$$

where $\mathbf{\Upsilon}$ is given by (A.18) in the Appendix.

2.2 Extensions

We have considered mean group estimation based on the (augmented) DL regressions (2). Other unit-specific estimation approaches could also be utilized in place of the DL regression specification. These include the LP approach popularized by Jordà (2005), or the iterative ARDL, VARDL, or VARX* approaches. See Choi and Chudik (2019) for a further discussion of the strengths and weaknesses of these approaches.

Another important consideration is the object of interest. In some empirical applications, the primary focus can be on the mean cumulative response,

$$\delta_{i,h} = \sum_{\ell=0}^{h} b_{i\ell},$$

where $\delta_{i,h}$ is also commonly referred to as the (mean) cumulative multiplier. These multipliers can be estimated by cumulating estimates of $b_{i\ell}$, namely

$$\hat{\delta}_{i,h} = \sum_{\ell=0}^{h} \hat{b}_{i\ell}.$$

Alternatively, these multipliers can be estimated directly using the augmented DL regressions applied to the variables generated by cumulating x_{ijt},

$$\xi_{ijt} = x_{ijt} + \xi_{i,j,t-1},$$

with the initial value ξ_{ij0} set to zero, without any loss of generality. Direct MGDL estimator of $\hat{\delta}_{i,h}$ can, for instance, be obtained using the following specification.

$$\xi_{ijt} = a_{ij} + \sum_{\ell=0}^{h} \delta_{ij\ell} v_{t-\ell} + \varphi_{hij} \xi_{i,j,t-h-1} + \theta_{hij} \Delta\xi_{i,j,t-h-1} + e_{hit}. \tag{15}$$

We have effectively included two lags of the dependent variable in (15) to facilitate the exposition in the MC section below, where we compare the direct and indirect MGDL estimators of $\delta_{i,h}$, assuming the random coefficient specification $\delta_{ij\ell} = \delta_{i,h} + c^{\delta}_{j,h} + \omega^{\delta}_{ij\ell}$ implied by Assumption 1.

3 Monte Carlo Evidence

This section investigates the small sample performance of the MGDL estimators of mean impulse-response coefficients $\mathbf{b}_i = (b_{i0}, b_{i1}, ..., b_{ih})'$ and the mean cumulative multipliers $\delta_{i,h} = \sum_{\ell=0}^{h} b_{i\ell}$. We set the horizon $h = 4$ matching the horizon selected in the empirical illustrations below. Subsections 3.1-3.3 respectively provide the Monte Carlo simulation design, the description of adopted estimators, and statistics of interest. The last subsection presents a summary of the Monte Carlo simulation results.

3.1 Simulation Design

We generate x_{ijt} based on (1), namely

$$x_{ijt} = a_{ij} + \sum_{\ell=0}^{\infty} b_{ij\ell} v_{t-\ell} + z_{ijt}, \quad \text{for } i = 1, 2, ..., M, \; j = 1, 2, ..., N, \text{ and } t = 1, 2, ..., T, \tag{16}$$

where the shock v_t is generated as $v_t \sim N(0, 1)$ and the fixed effects are generated as $a_{ij} \sim N(1, 1)$. z_{ijt} is generated to be persistent as

$$z_{ijt} = \rho_{ij} z_{ij,t-1} + \sqrt{1 - \rho_{ij}^2} e_{ijt},$$

for $t = -B + 1, -B + 2, ..., 0, 1, 2, ..., T$, in which $B = 100$, and there are two choices forρ_{ij}: (i) $\rho_{ij} \sim U[0.3, 0.5]$ (denoted as $\rho_{\max} = 0.5$) and (ii) $\rho_{ij} \sim U[0.6, 0.95]$ (denoted as $\rho_{\max} = 0.95$). We generate e_{ijt} according to

$$e_{ijt} = \gamma_{ij} f_t + \varepsilon_{ijt},$$

where $f_t \sim N(0,1)$, $\gamma_{ij} = U[0, 0.2]$, and $\varepsilon_{ijt} \sim N(0,1)$.

The IRF coefficients, $b_{ij\ell}$, are generated based on the following random coefficient specification,

$$b_{ij\ell} = b_{i\ell} + c_{j\ell} + \omega_{ij\ell},$$

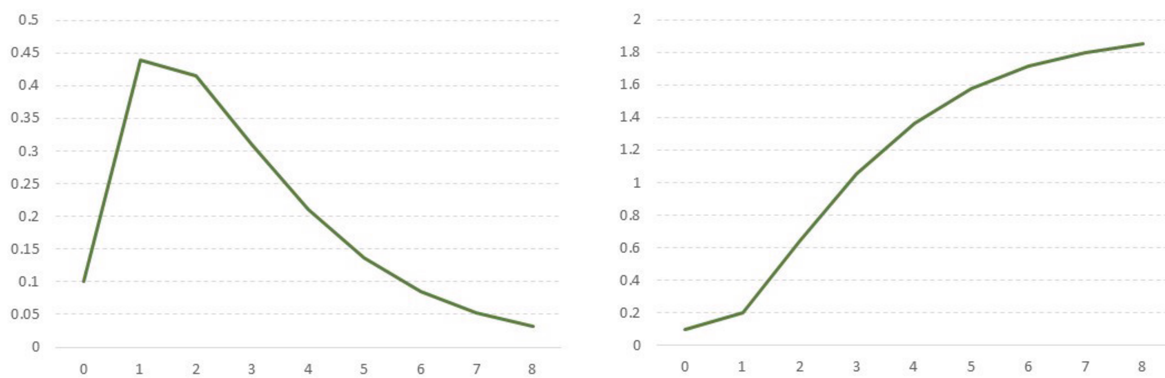
for $\ell = 1, 2, ..., B$, where $B = 100$,

$$b_{i\ell} = H_1 \lambda_1^{\ell} + H_2 \lambda_2^{\ell},$$

$\lambda_1 = 0.6$, $\lambda_2 = 0.4$, $H_1 = 2$ and $H_2 = -1.9$. This parameterization resembles a hump-shaped IRF that is common in many applications (see Figure 1 for plots of $b_{i\ell}$ and $\delta_{i,h} = \sum_{\ell=0}^{h} b_{i\ell}$).

Figure 1: Plots of $b_{i\ell}$ and the cumulative multipliers ($\delta_{i,h} = \sum_{\ell=0}^{h} b_{i\ell}$)

(a) Plot of $b_{i\ell}$, $\ell = 0, 1, ..., 8$ (b) Plot of $\delta_{i,h} = \sum_{\ell=0}^{h} b_{i\ell}$, $h = 0, 1, ..., 8$



We generate $c_{j\ell} = 0.1\kappa_\ell \alpha_j$, $\kappa_\ell = 0.8^{\ell}$, and $\alpha_j = 1 - 2(j-1)/(N-1)$ which ensures $\sum_{j=1}^{N} c_{j\ell} = 0$, as required for identification. $\omega_{ij\ell}$ is generated as $\omega_{ij\ell} = \kappa_\ell \times \Delta_{ij}$, where $\Delta_{ij} \sim U[-0.2, 0.2]$. We set $b_{ij\ell} = 0$ for $\ell > B$ (and $B = 100$). Note that due to exponential decay, $b_{ij\ell}$ are all negligible for a larger value of ℓ.

We consider $M = N \in \{30, 40, 50, 100\}$, and $T = \{50, 100, 150, 200\}$ and compute $R = 2000$ Monte Carlo replications.

3.2 Estimators

For the estimation of $b_{i\ell}$, we consider the MGDL estimator given by (3) based on the augmented DL regressions (2) with $\mathbf{g}_{hijt}$ given by $x_{i,j,t-h-1}$, namely the estimating regression is

$$x_{ijt} = a_{ij} + \sum_{\ell=0}^{h} b_{ij\ell} v_{t-\ell} + \varphi_{hij} x_{i,j,t-h-1} + e_{hit}. \tag{17}$$

For the estimation of the cumulative multiplier ($\delta_{i,h}$), we consider cumulating the MGDL estimates, namely $\hat{\delta}_{i,h} = \sum_{\ell=0}^{h} \hat{b}_{i\ell}$. Furthermore, we investigate three direct options for the estimation of $\delta_{i,h}$ discussed in Section 2.2, based on (15) with or without restrictions imposed on $\left(\varphi_{hij}, \theta_{hij}\right)$. The first specification imposes $\theta_{hij} = 0$ and is given by

$$\xi_{ijt} = a_{ij} + \sum_{\ell=0}^{h} \delta_{ij\ell} v_{t-\ell} + \varphi_{hij} \xi_{i,j,t-h-1} + e_{hit}, \tag{18}$$

The second specification imposes $\varphi_{hij} = 1$ and $\theta_{hij} = 0$, namely

$$\xi_{ijt} = a_{ij} + \sum_{\ell=0}^{h} \delta_{ij\ell} v_{t-\ell} + \xi_{i,j,t-h-1} + e_{hit}. \tag{19}$$

The third specification imposes $\varphi_{hij} = 1$ only,

$$\xi_{ijt} = a_{ij} + \sum_{\ell=0}^{h} \delta_{ij\ell} v_{t-\ell} + \xi_{i,j,t-h-1} + \theta_{hij} \Delta\xi_{i,j,t-h-1} + e_{hit}. \tag{20}$$

Confidence intervals are based on two options for the asymptotic variance estimators: (i) the nonparametric estimator in (7) and (ii) the augmented estimator given by (9). We use Bonferroni correction to control for the family-wise error rate, as proposed by Dunn (1961).

3.3 Objectives

Our focus here is twofold: (i) the estimation of $b_{i\ell}$; and (ii) the estimation of the cumulative multiplier $\delta_{i,h} = \sum_{\ell=0}^{h} b_{i\ell}$. Regarding the first objective, we report the overall estimation bias computed as

$$bias_b = \frac{1}{(h+1)\,NR}\sum_{r=1}^{R}\sum_{i=1}^{N}\sum_{\ell=0}^{h}\left(\hat{b}_{i\ell}^{(r)} - b_{i\ell}\right), \tag{21}$$

the overall RMSE computed as

$$rmse_b = \left[\frac{1}{(h+1)\,NR}\sum_{r=1}^{R}\sum_{i=1}^{N}\sum_{\ell=0}^{h}\left(\hat{b}_{i\ell}^{(r)} - b_{i\ell}\right)^2\right]^{1/2}, \tag{22}$$

and the 95% family-wise (across both $\ell = 0, 1, ..., h$ and $i = 1, 2, ..., N$) confidence intervals coverage rate

$$FWCR_{b,0.95} = \frac{1}{R}\sum_{r=1}^{R} I\left\{\sum_{i=1}^{N}\sum_{\ell=0}^{h} I\left[\hat{b}_{i\ell}^{(r)} \in CI\left(\hat{b}_{i\ell}^{(r)}\right)\right] = N\,(h+1)\right\}, \tag{23}$$

where $CI\left(\hat{b}_{i\ell}^{(r)}\right)$ is the 95% family-wise confidence interval for $\hat{b}_{i\ell}^{(r)}$.

In the case of estimation of the cumulative multiplier $\delta_{i,h}$, we focus on $h = 4$, and report the bias,

$$bias_{\delta,h} = \frac{1}{NR}\sum_{r=1}^{R}\sum_{i=1}^{N}\left(\hat{\delta}_{i,h}^{(r)} - \delta_{i,h}\right), \tag{24}$$

the RMSE

$$rmse_{\delta,h} = \left[\frac{1}{NR}\sum_{r=1}^{R}\sum_{i=1}^{N}\left(\hat{\delta}_{i,h}^{(r)} - \delta_{i,h}\right)^2\right]^{1/2}, \tag{25}$$

as well as the 95% family-wise (across $i = 1, 2, ..., N$) confidence intervals coverage rate.

$$FWCR_{\delta,h,0.95} = \frac{1}{R}\sum_{r=1}^{R} I\left[\sum_{i=1}^{N} I\left[\hat{\delta}_{i,h}^{(r)} \in CI\left(\hat{\delta}_{i,h}^{(r)}\right)\right] = N\right]. \tag{26}$$

3.4 Monte Carlo Simulation Results

Table 1 summarizes the simulation results for the bias ($bias_b \times 100$), RMSE ($rmse_b \times 100$), and the family-wise coverage rates of the 95% confidence intervals ($FWCR_{b,0.95} \times 100$) for the estimation of non-cumulative IRF parameters $\mathbf{b}_i$. Coverage Rate 1 is based on (7), and it is therefore likely to perform well only when $M/T \to 0$ and $N/T \to 0$, see (5). When M, N, T are of the same order, we expect these confidence intervals to underestimate the true extent of estimation uncertainty due to the strong cross-section dependence. Coverage Rate 2 is based on (9), and it is therefore applicable when M, N, T are of the same order, see (6), and it is robust to strong cross-section dependence.

Overall, the bias of the MGDL estimator is small and diminishes with T. Coverage Rate 1 show inference based on the usual nonparametric formula (7) significantly underestimate the true extent of uncertainty. This coverage rate improves for a fixed N, M, as T increases, but is overall very low for the sample sizes considered. Coverage Rate 2 is close to the 95 percent, slightly overestimating the uncertainty, as expected due to conservative Bonferroni correction by Dunn (1961). The choice of persistence ($\rho_{\max} = 0.5$ or 0.95) turns out to be broadly inconsequential to the performance of the MGDL estimator in the experiment designs considered here.

Tables 2 and 3 present the results for the estimation of the cumulative multiplier $\delta_{i,h}$ (for $h = 4$) in experiments with $\rho_{\max} = 0.5$ and 0.95, respectively. Regardless of the choice of $\rho_{\max}$, the direct estimators of $\delta_{i,4}$ based on regressions (18)-(20) have consistently poorer performances in terms of the bias, RMSE, and the coverage rates, compared to the indirect estimation based on (17). The RMSE difference between the direct and indirect estimators is strikingly large, in the range of 46 and 290 percent for $T = 50$. Although the performance gap between the two approaches diminishes with an increase in T, it still remains large even for $T = 200$. This outcome leads us to focus on the indirect estimators of the cumulative multiplier in the empirical illustrations in the next section. Overall, our Monte Carlo experiments show satisfactory performance of the MGDL estimators for the IRF means $\mathbf{b}_i$ and their cumulative sums.

Table 1: MC results for the estimation of $\mathbf{b}_i$ in experiments with low and high persistence ($\rho_{\max} = 0.5$ and $\rho_{\max} = 0.95$)

	Bias (×100)				RMSE (×100)				Coverage Rate 1 (%)				Coverage Rate 2 (%)			
T:	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**
	(a) Experiments with low persistence ($\rho_{\max} = 0.5$)															
$N = M$	MGDL															
30	-0.49	-0.25	-0.18	-0.14	5.42	4.52	4.23	4.06	55.20	68.35	74.25	80.05	97.65	97.80	96.95	97.15
40	-0.55	-0.23	-0.15	-0.09	4.87	3.99	3.72	3.60	50.45	64.20	73.60	77.35	98.00	98.05	97.20	98.25
50	-0.64	-0.22	-0.16	-0.13	4.53	3.64	3.39	3.25	44.90	62.00	72.55	74.80	97.70	98.15	98.40	97.45
100	-0.60	-0.23	-0.13	-0.13	3.71	2.83	2.56	2.43	26.15	43.30	56.90	63.55	97.30	98.60	98.90	98.80
	(b) Experiments with high persistence ($\rho_{\max} = 0.95$)															
	MGDL															
30	-0.14	-0.05	-0.03	-0.02	5.28	4.45	4.20	4.04	60.35	71.10	77.00	81.75	97.95	97.45	96.75	96.90
40	-0.18	-0.03	-0.02	0.01	4.71	3.93	3.68	3.58	55.25	68.25	76.55	80.25	97.95	98.05	97.40	98.05
50	-0.27	-0.02	-0.03	-0.02	4.35	3.58	3.35	3.23	51.85	65.90	74.55	76.95	97.60	98.00	98.25	97.35
100	-0.24	-0.03	0.00	-0.04	3.52	2.75	2.53	2.41	32.00	48.40	59.75	67.80	97.75	98.70	98.85	98.75

Notes: This table reports the overall bias and RMSE (both ×100), as defined in (21) and (22), respectively, and the family-wise coverage rate of Bonferroni-corrected 95 percent confidence intervals, as defined by (23) computed using the usual nonparametric variance estimator (7) (Coverage Rate 1) and the augmented variance estimator (9) (Coverage Rate 2). The MGDL estimator is based on augmented DL regressions (17). Reported results are based on $R = 2000$ Monte Carlo replications.

Table 2: MC results for the estimation of the cumulative multiplier $\delta_{i,h}$ ($h = 4$) in experiments with low persistence ($\rho_{\max} = 0.5$)

	Bias (×100)				**RMSE (×100)**				**Coverage Rate 1 (%)**				**Coverage Rate 2 (%)**			
T:	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**
$N = M$	(a) MGDL estimation based on (17), $\hat{\delta}_{i,h} = \sum_{\ell=0}^{h} \hat{b}_{i\ell}$															
30	-2.43	-1.27	-0.89	-0.68	21.71	19.42	18.74	18.26	75.95	80.50	81.80	85.10	84.70	86.40	85.75	87.70
40	-2.74	-1.14	-0.73	-0.43	19.38	16.99	16.36	16.11	74.65	82.25	83.95	85.30	84.55	88.15	87.45	88.60
50	-3.18	-1.11	-0.82	-0.66	17.91	15.32	14.78	14.43	74.05	82.90	84.80	85.70	84.25	88.80	89.30	89.35
100	-3.01	-1.17	-0.65	-0.67	14.28	11.48	10.80	10.49	64.55	77.70	83.20	86.45	81.80	87.55	90.20	91.20
	(b) Direct MGDL estimation based on (18)															
30	-34.59	-16.73	-10.23	-7.39	56.22	38.64	31.21	27.47	19.25	30.85	42.05	49.95	62.70	78.35	83.00	85.55
40	-36.77	-15.56	-9.97	-6.96	56.10	37.03	29.48	26.59	18.10	28.90	37.75	42.85	62.85	81.30	86.65	87.55
50	-37.21	-16.06	-10.51	-8.21	55.82	36.12	29.60	25.70	16.10	27.15	33.20	38.65	66.60	82.25	86.00	87.60
100	-37.03	-16.10	-10.44	-7.52	55.62	34.23	27.12	24.08	10.45	18.50	24.95	29.55	70.90	87.45	91.10	91.85
	(c) Direct MGDL estimation based on (19)															
30	-10.16	-5.65	-3.18	-2.41	39.41	30.36	26.01	23.70	34.45	45.15	54.05	62.25	82.80	87.15	89.55	89.90
40	-11.62	-4.57	-2.85	-1.96	37.97	28.64	24.04	22.40	29.85	40.55	50.10	53.95	83.55	88.75	90.60	91.65
50	-12.33	-5.41	-3.57	-3.03	37.64	27.07	23.64	21.26	28.20	39.00	46.65	50.10	83.65	89.40	90.20	91.20
100	-12.03	-4.92	-3.25	-2.45	36.66	25.26	20.52	19.05	20.65	29.70	34.90	39.20	88.80	93.15	94.95	94.30
	(d) Direct MGDL estimation based on (20)															
30	-7.04	-3.51	-2.06	-1.39	31.75	24.61	22.02	20.60	46.65	59.05	67.75	73.55	84.60	88.70	89.40	90.80
40	-7.96	-2.95	-1.66	-1.14	30.00	22.60	19.93	18.83	42.10	56.85	65.85	69.40	84.85	89.80	91.65	92.10
50	-8.51	-3.51	-2.22	-1.94	29.45	21.13	18.82	17.47	39.05	55.65	62.50	67.15	86.00	90.35	91.20	91.60
100	-8.19	-3.07	-1.94	-1.63	27.60	18.45	15.44	14.35	29.00	43.00	52.25	55.50	87.90	93.65	94.95	94.10

Notes: This table reports the bias and RMSE (both ×100), defined in (24) and (25), respectively, and the Bonferroni-corrected family-wise coverage rate of 95 percent confidence intervals defined in (26) computed using the usual nonparametric variance estimator (7) (Coverage Rate 1) and the augmented variance estimator (9) (Coverage Rate 2). Reported results are based on $R = 2000$ Monte Carlo replications.

Table 3: MC results for the estimation of the cumulative multiplier $\delta_{i,h}$ $(h = 4)$ in experiments with high persistence $(\rho_{\max} = 0.95)$

	Bias (×100)				**RMSE (×100)**				**Coverage Rate 1 (%)**				**Coverage Rate 2 (%)**			
T:	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**	**50**	**100**	**150**	**200**
$N = M$	(a) MGDL estimation based on (17), $\hat{\delta}_{i,h} = \sum_{\ell=0}^{h} \hat{b}_{i\ell}$															
30	-0.72	-0.26	-0.14	-0.09	21.95	19.55	18.87	18.36	78.70	81.90	83.15	86.10	85.80	87.25	85.95	88.25
40	-0.91	-0.16	-0.10	0.07	19.45	17.07	16.41	16.19	77.00	83.55	86.10	86.15	85.90	88.75	89.00	89.10
50	-1.37	-0.09	-0.14	-0.10	17.74	15.40	14.81	14.51	77.80	85.30	86.35	86.10	86.55	89.70	90.15	89.20
100	-1.19	-0.15	0.00	-0.22	13.87	11.34	10.78	10.48	69.75	81.05	85.25	87.60	83.80	89.35	91.45	91.90
	(b) Direct MGDL estimation based on (18) (φ is not restricted)															
30	-34.42	-16.61	-10.10	-7.33	56.40	38.89	31.43	27.64	20.80	32.00	43.75	49.50	63.10	79.25	84.10	86.25
40	-36.55	-15.40	-9.96	-6.89	56.19	37.23	29.70	26.74	18.40	29.50	38.05	43.20	63.25	80.90	86.60	87.70
50	-36.94	-16.00	-10.43	-8.14	55.87	36.30	29.75	25.85	16.85	28.30	34.05	38.60	65.45	81.75	85.90	87.65
100	-36.76	-15.94	-10.32	-7.49	55.54	34.28	27.19	24.18	11.30	19.35	26.10	30.60	70.35	87.65	91.05	92.25
	(c) Direct MGDL estimation based on (19) (φ is restricted to one)															
30	-10.16	-5.64	-3.12	-2.39	39.79	30.66	26.25	23.85	35.50	45.55	55.05	61.00	82.50	87.40	89.85	90.50
40	-11.62	-4.54	-2.88	-1.93	38.29	28.92	24.26	22.55	31.35	41.10	51.10	54.35	83.35	89.05	91.05	91.90
50	-12.32	-5.45	-3.57	-3.01	37.93	27.31	23.82	21.42	30.15	40.05	47.00	50.15	82.95	89.05	90.40	90.95
100	-12.01	-4.87	-3.20	-2.47	36.84	25.40	20.63	19.16	20.85	29.70	35.45	39.65	87.90	92.95	94.85	94.20
	(d) Direct MGDL estimation based on augmented regression (20)															
30	-4.91	-2.18	-1.27	-0.75	30.21	23.83	21.60	20.36	50.25	62.15	70.20	75.55	86.85	91.30	90.45	92.20
40	-5.56	-1.80	-0.86	-0.55	28.21	21.74	19.56	18.51	46.95	60.05	67.95	71.05	87.15	91.50	92.85	93.50
50	-6.07	-2.33	-1.37	-1.29	27.29	20.30	18.29	17.09	43.55	56.60	65.00	69.75	88.75	92.75	92.40	92.60
100	-5.66	-1.82	-1.09	-1.06	25.27	17.37	14.88	13.83	32.10	45.35	54.70	59.50	89.95	94.85	95.70	95.10

Notes: See the notes in Table 2.

4 Empirical Illustrations

This section presents three brief empirical illustrations. The first two illustrations utilize quarterly retail price data provided by the Council for Community and Economic Research (C2ER, https://www.c2er.org/redt/), formerly known as American Chamber of Commerce Researchers Association. Originally created for comparing the cost of living for mid-level managers in various metropolitan areas in the U.S., the C2ER dataset contains retail prices of a large number of individual goods and services in dollars and cents (see Choi, Choi, and Chudik (2020)). This dataset covers retail prices for 43 products ($M = 43$) in 41 metropolitan areas ($N = 41$), spanning from the first quarter of 1990 to the fourth quarter of 2015 ($T = 104$). We consider the effects of crude oil price shocks (Subsection 4.1) and the effects of U.S. monetary policy shocks (Subsection 4.2). Our third empirical illustration explores the impacts of U.S. monetary policy shocks on house prices by utilizing a panel dataset consisting of 404 metropolitan areas ($N = 404$) from the first quarter of 1975Q1 to the fourth quarter of 2023 (Subsection 4.3).

4.1 The Impact of Oil Price Shocks on Retail Prices

We investigate the impacts of crude oil price shocks, computed as the first difference of log of crude oil prices sequentially sampled at the end of each quarter, on the city- and product-level retail prices.[3] To this end, we utilize the daily West Texas Intermediate (WTI) crude oil prices obtained from FRED database (https://fred.stlouisfed.org, series DCOILWTICO). We focus on the cumulative multipliers of the oil shock, measured at the horizon of $h = 4$ quarters.

Guided by the MC results in Section 3, we employ the MGDL approach based on (17) as opposed to equations (18)-(20). In addition to the lagged dependent variable, $x_{i,j,t-h-1}$, we also augment (17) with seasonal dummies. Table 4 reports the estimates of cumulative multipliers, $\hat{\delta}_{i,h} = \sum_{\ell=0}^{h} \hat{b}_{i\ell}$, together with Bonferroni-corrected 95% family-wise confidence intervals. These intervals are based on the augmented variance estimators given by (9)-(10) that are robust to strong cross-section dependence. Significant entries are highlighted by asterisks. Not surprisingly, in retail gasoline price (product #26) we note a large pass-through effect of oil price shocks at

[3] First-differenced logs of sequentially sampled crude oil prices do not contain any statistically significant serial correlation.

62.7%, meaning a 1% rise in WTI crude oil prices results in an approximate 0.6% increase in retail gasoline prices across US cities, on average. Given that the long-run pass-through estimate of 62.7% is approximately the cost share of crude oil of producing gasoline (Baumeister and Kilian (2014)), our results indicate a full pass-through. Further inspection of the impulse response coefficients $\hat{b}_{i\ell}$ suggests that the full pass-through takes place within one quarter, in line with our economic intuition. However, we find that crude oil price pass-through is not statistically significant in the remaining products, with a single exception of the "shortening". The estimates of location effects (c_j) are reported in Table A1 in the Appendix, which are economically very small and insignificant in the vast majority of locations under study.

4.2 The Effects of Monetary Policy Shocks on Retail Prices

We investigate the effects of U.S. monetary policy shocks next using the same retail price panel. For this exercise, we borrow five popular measures of U.S. monetary policy shocks by Bu, Rogers, and Wu (2021, BRW), Aruoba and Drechsel (2022, AD), Romer and Romer (2004, RR) updated by Wieland (2021), Nakamura and Steinsson (2018, NS), and the target monetary policy shock by Gürkaynak, Sack, and Swanson (2005, GSS). These shocks are scaled to have a unit variance and a positive correlation with the one-day change in the one-year Treasury yield around the FOMC announcement, as in Acosta (2023). Not surprisingly, these measures are positively correlated with the correlation, in the wide range of 20 to 72 percent (see Table 5).

MGDL estimates of the cumulative retail price effects of these shocks are presented in Table A2 in the Appendix. Surprisingly, we do not find any statistically significant effects, for any product category and any of the five shocks. This could be due to the possibility that U.S. monetary policy shocks explain only a small fraction of retail price fluctuations. Furthermore, the monetary policy shocks are imperfectly measured, and the retail price data are noisy as well.

Table 4: Estimates of oil price shocks cumulative multipliers ($h = 4$)

		MGDL	
	Product category	$\hat{\delta}_{i,4}$	Conf. Interval$^{\diamond}$
1	TBONESTEAK	0.056	[-0.055,0.167]
2	GROUNDBEEF	0.023	[-0.128,0.173]
3	FRYINGCHICKEN	-0.012	[-0.118,0.094]
4	CANNED TUNA	-0.086	[-0.231,0.059]
5	WHOLEMILK	0.101	[-0.041,0.244]
6	EGGS	0.095	[-0.246,0.436]
7	MARGARINE	-0.034	[-0.163,0.094]
8	CHEESE	0.002	[-0.101,0.105]
9	POTATOES	0.002	[-0.359,0.363]
10	BANANAS	0.109	[-0.084,0.302]
11	LETTUCE	0.012	[-0.443,0.468]
12	BREAD	0.073	[-0.042,0.189]
13	COFFEE	0.108	[-0.106,0.322]
14	SUGAR	0.014	[-0.111,0.139]
15	CORNFLAKES	-0.005	[-0.103,0.092]
16	CANNED PEAS	-0.019	[-0.163,0.126]
17	CANNED PEACHES	-0.015	[-0.094,0.063]
18	TISSUES	0.087	[-0.059,0.233]
19	DETERGENT	-0.174	[-0.385,0.037]
20	SHORTENING	0.222*	[0.080,0.364]
21	FROZEN CORN	0.066	[-0.096,0.228]
22	SOFT DRINK	0.013	[-0.077,0.103]
23	HOME PRICE	0.000	[-0.034,0.035]
24	PHONE	0.019	[-0.038,0.075]
25	AUTO MAINTENANCE	-0.418	[-0.880,0.043]
26	GASOLINE	0.627*	[0.356,0.897]
27	DOCTOR VISIT	-0.005	[-0.067,0.058]
28	DENTIST VISIT	-0.055	[-0.187,0.077]
29	MCDONALD'S HAMBURGER	-0.001	[-0.056,0.054]
30	PIZZA	-0.022	[-0.108,0.064]
31	FRIED CHICKEN	0.005	[-0.067,0.077]
32	HAIRCUT	0.003	[-0.045,0.051]
33	BEAUTY SALON	0.007	[-0.071,0.085]
34	TOOTHPASTE	-0.002	[-0.113,0.108]
35	DRY CLEANING	-0.008	[-0.057,0.042]
36	MAN'S SHIRT	-0.077	[-0.246,0.091]
37	APPLIANCE REPAIR	0.017	[-0.052,0.087]
38	NEWSPAPER	-0.016	[-0.089,0.056]
39	MOVIE	0.005	[-0.035,0.045]
40	BOWLING	0.006	[-0.070,0.081]
41	TENNIS BALLS	-0.016	[-0.100,0.068]
42	BEER	0.119	[-0.035,0.272]
43	WINE	0.058	[-0.062,0.178]

Notes: ($^{\diamond}$) 95 percent family-wise confidence intervals are reported.
(*) Statistically significant estimates are highlighted by asterisk.

This table reports the MGDL cumulative multiplier estimates $\hat{\delta}_{i,h} = \sum_{\ell=0}^{h} \hat{b}_{i\ell}$ at horizon $h = 4$ quarters for the crude oil price shocks. MGDL estimates are based on augmented DL regressions (17), where x_{ijt} is log-difference of price for product category i in city j in period t from C2ER dataset, which spans $M = 43$ reported categories over $N = 41$ cities, covering $T = 104$ quarterly periods from 1990Q1 to 2015Q4.

Table 5: Correlations among U.S. monetary policy shocks measures

	BRW	AD	RR	NS	GSS
BRW	1.00	0.24	0.22	0.54	0.30
AD	.	1.00	0.72	0.28	0.47
RR	.	.	1.00	0.20	0.36
NS	.	.	.	1.00	0.62
GSS	.	.	.	.	1.00

Notes: This table presents correlation matrix of U.S. monetary policy shocks by Bu, Rogers, and Wu (2021, BRW), Aruoba and Drechsel (2022, AD), Romer and Romer (2004, RR) updated by Wieland (2021), Nakamura and Steinsson (2018, NS), and Gürkaynak, Sack, and Swanson (2005, GSS), aggregated to quarterly frequency.

Table 6: Estimates of US monetary policy cumulative multipliers ($h = 4$) on house prices

MP Shock	$\hat{\delta}_{i,4}$	Conf. Interval
BRW	0.644*	[0.261,1.026]
AD	0.313	[-0.026,0.652]
RR	0.050	[-0.214,0.314]
NS	0.633*	[0.241,1.025]
GSS	0.854*	[0.454,1.255]

Notes: See notes to Table 5. MGDL estimates are obtained based on (17) augmented with seasonal dummies.

4.3 The Effects of U.S. Monetary Policy Shocks on House Prices

In light of the lack of statistically significant effects of monetary policy shocks on retail prices, we investigate the effects on house prices in a quarterly panel featuring $N = 404$ metropolitan areas. This dataset is less noisy and has a better time coverage (1975Q1 to 2023Q4). Table 6 presents estimates of cumulative multipliers of monetary policy shocks. All five estimates are positive and three are statistically significant (BRW, NS and GSS). The estimation results suggest that unit (one standard deviation) contractionary monetary policy shock leads to 0.6-0.9 percent house price appreciation one year after the shock. Monetary policy shocks affect both demand and supply side of housing market and these estimates suggest that, perhaps due to the dominant supply side effects, contractionary monetary policy effects could lead to house price appreciation.

5 Conclusion

This paper developed the MGDL estimators of impulse-responses in a panel setting with one or two cross-sections under assumptions that the shock is common, observed, and the impulse responses follow a random coefficient specification. We obtained sufficient conditions for asymptotic normality, and documented satisfactory small sample performance using Monte Carlo experiments. The empirical relevance of the MGDL estimators is showcased by examining crude oil price pass-through on U.S. retail prices, as well as the effects of U.S. monetary policy shocks on the retail prices and on the house prices.

Several potential extensions remain for future research. Specifically, within the context of panel data, alternative methodologies beyond the distributed lag specifications investigated in this paper warrant further exploration. Some of these alternative approaches mentioned in Section 2.2 may yield panel estimators with improved performance in small samples. Of theoretical interest is also the case of homogenous IRFs, although such homogeneity assumption appears less plausible for empirical applications. We abstracted from time aggregation issues, but there could be a frequency mismatch between the shock variable and the target variable of interest. Contrasting panel estimators with estimation based on the aggregated data is also of interest. In addition, estimation of IRFs for unit-specific (as opposed to common) shocks could be considered, as in Mei, Sheng, and Shi (2023). We leave exploration of these avenues to future studies.

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A Appendix

This appendix consists of two sections. Section A.1 presents lemmas and proofs. Section A.2 presents additional empirical results.

A.1 Lemmas and Proofs

Lemma A.1 *Let $\boldsymbol{\epsilon}_{ij} = \hat{\mathbf{b}}_{ij} - \mathbf{b}_{ij}$, and assume Assumptions 1-3 hold, where $\hat{\mathbf{b}}_{ij}$ is the LS estimator of $(h+1) \times 1$ vector $\mathbf{b}_{ij} = (b_{ij0}, b_{ij1}, ..., b_{ijh})'$ in the DL regression (2). Then*

$$N^{-1/2} \sum_{j=1}^{N} \boldsymbol{\epsilon}_{ij} \rightarrow_d N\left(0, \kappa_1 \boldsymbol{\Upsilon}_{1,i}\right), \tag{A.1}$$

and

$$M^{-1/2} \sum_{i=1}^{M} \left(\boldsymbol{\epsilon}_{ij} - \bar{\boldsymbol{\epsilon}}_{i\circ}\right) \rightarrow_d N\left(0, \kappa_2 \boldsymbol{\Upsilon}_{2,j}\right) \tag{A.2}$$

as $(M, N, T) \rightarrow \infty$ jointly such that $N/T \rightarrow \kappa_1 > 0$ and $M/T \rightarrow \kappa_2 > 0$, where

$$\boldsymbol{\Upsilon}_{1,i} = \frac{\varkappa_{hi}}{\sigma_v^2} \mathbf{I}_{h+1}, \tag{A.3}$$

$$\boldsymbol{\Upsilon}_{2,j} = \frac{\pi_{hj}}{\sigma_v^2} \mathbf{I}_{h+1}, \tag{A.4}$$

$\sigma_v^2 = E\left(v_t^2\right)$, and $(\varkappa_{ehi}, \pi_{hj})$ are defined in Assumption 3.

Proof. Define $\mathbf{x}_{ij} = (x_{ij,h+1}, x_{ij,h+2}, ..., x_{ijT})'$, $\mathbf{v}_\ell = (v_{h+1-\ell}, v_{h+2-\ell}, ..., v_{T-\ell})'$ for $\ell = 0, 1, 2, ..., h$, $\mathbf{e}_{hij} = (e_{h,i,j,h+1}, e_{h,i,j,h+2}, ..., e_{h,i,j,T})'$, and let $\boldsymbol{\tau}$ be the $T-h \times 1$ vector of ones. Define also the $T-h \times (h+1)$ matrix $\mathbf{V} = (\mathbf{v}_0, \mathbf{v}_1, ..., \mathbf{v}_h)'$ and the $T-h \times k_g$ matrix $\mathbf{G}_{hij} = (\mathbf{g}_{hij,h+1}, \mathbf{g}_{hij,h+2}, ..., \mathbf{g}_{hij,T})'$. Vectors $\mathbf{x}_{ij}$, $\mathbf{v}_\ell$, $\mathbf{e}_{hij}$, and $\boldsymbol{\tau}$, and the matrices $\mathbf{V}$ and $\mathbf{G}_{hij}$ all depend on T, but the subscript T is omitted to simplify the notations.

The DL regression (2) can be written

$$\mathbf{x}_{ij} = \boldsymbol{\tau} a_{ij} + \mathbf{V}\mathbf{b}_{ij} + \mathbf{G}_{hij}\boldsymbol{\varphi}_{hij} + \mathbf{e}_{hij}, \tag{A.5}$$

Let $\tilde{\mathbf{G}}_{hij} = (\boldsymbol{\tau}, \mathbf{G}_{hij})$, $\mathbf{M}_{hij} = \mathbf{I}_{T-h} - \tilde{\mathbf{G}}_{hij}\left(\tilde{\mathbf{G}}'_{hij}\tilde{\mathbf{G}}_{hij}\right)^{-1}\tilde{\mathbf{G}}_{hij}$, $\tilde{\mathbf{x}}_{ij} = \mathbf{M}_{hij}\mathbf{x}_{ij}$, $\tilde{\mathbf{V}} = \mathbf{M}_{hij}\mathbf{V}$ and $\tilde{\mathbf{e}}_{hij} = \mathbf{M}_{hij}\mathbf{e}_{hij}$. Multiplying the above DL regression by $\mathbf{M}_{hij}$ we obtain

$$\tilde{\mathbf{x}}_{ij} = \tilde{\mathbf{V}}\mathbf{b}_{ij} + \tilde{\mathbf{e}}_{hij}.$$

The LS estimator $\hat{\mathbf{b}}_{ij}$ is $\hat{\mathbf{b}}_{ij} = \left(\tilde{\mathbf{V}}'\tilde{\mathbf{V}}\right)^{-1}\tilde{\mathbf{V}}'\tilde{\mathbf{x}}_{ij}$, and

$$\boldsymbol{\epsilon}_{ij} = \hat{\mathbf{b}}_{ij} - \mathbf{b}_{ij} = \left(\tilde{\mathbf{V}}'\tilde{\mathbf{V}}\right)^{-1}\tilde{\mathbf{V}}'\tilde{\mathbf{e}}_{hij}.$$

Since $\mathbf{M}_{hij}$ is symmetric and idempotent, it follows $\mathbf{M}'_{hij}\mathbf{M}_{hij} = \mathbf{M}_{hij}$. Consider $N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}$. We have

$$\begin{aligned} N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij} &= N^{-1/2}\sum_{j=1}^{N}\left(\tilde{\mathbf{V}}'\tilde{\mathbf{V}}\right)^{-1}\tilde{\mathbf{V}}'\tilde{\mathbf{e}}_{hij} \\ &= \left(\frac{\tilde{\mathbf{V}}'\tilde{\mathbf{V}}}{T-h}\right)^{-1}\left(\frac{N}{T-h}\right)^{1/2}\frac{1}{N}\sum_{j=1}^{N}\frac{\tilde{\mathbf{V}}'\tilde{\mathbf{e}}_{hij}}{\sqrt{T-h}} \\ &= \left(\frac{\mathbf{V}'\mathbf{M}_{hij}\mathbf{V}}{T-h}\right)^{-1}\left(\frac{N}{T-h}\right)^{1/2}\frac{\mathbf{V}'\mathbf{M}_{hij}\bar{\mathbf{e}}_{hi\circ}}{\sqrt{T-h}}, \end{aligned} \tag{A.6}$$

where $\bar{\mathbf{e}}_{hi\circ} = \frac{1}{N}\sum_{j=1}^{N}e_{hij}$. Under Assumption 3,

$$\frac{\mathbf{V}'\mathbf{M}_{hij}\mathbf{V}}{T-h} \to_p \sigma_v^2\mathbf{I}_{h+1}, \tag{A.7}$$

and

$$\frac{\mathbf{V}'\mathbf{M}\bar{\mathbf{e}}_{hi\circ}}{\sqrt{T-h}} \to_d N\left(0, \sigma_v^2\varkappa_{hi}\mathbf{I}_{h+1}\right). \tag{A.8}$$

Using (A.7) and (A.8) in (A.6), and noting that $N/T \to \kappa_1$, we obtain

$$N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij} \to_d N\left(0, \kappa_1\boldsymbol{\Upsilon}_{i\circ}\right),$$

where $\boldsymbol{\Upsilon}_{i\circ} = \mathbf{I}_{h+1}\varkappa_{hi}/\sigma_v^2$. This completes the proof of result (A.1).

Consider $M^{-1/2}\sum_{i=1}^{M}(\boldsymbol{\epsilon}_{ij}-\bar{\boldsymbol{\epsilon}}_{i\circ})$ next. We have

$$\begin{aligned} M^{-1/2}\sum_{i=1}^{M}(\boldsymbol{\epsilon}_{ij}-\bar{\boldsymbol{\epsilon}}_{i\circ}) &= M^{-1/2}\sum_{i=1}^{M}\left(\tilde{\mathbf{V}}'\tilde{\mathbf{V}}\right)^{-1}\tilde{\mathbf{V}}'(\mathbf{e}_{hij}-\bar{\mathbf{e}}_{hi\circ}) \\ &= \left(\frac{\mathbf{V}'\mathbf{M}_{hij}\mathbf{V}}{T-h}\right)^{-1}\left(\frac{M}{T-h}\right)^{1/2}\frac{\mathbf{V}'\mathbf{M}_{hij}(\bar{\mathbf{e}}_{h\circ j}-\bar{\mathbf{e}}_{h\circ\circ})}{\sqrt{T-h}}, \end{aligned} \tag{A.9}$$

where by Assumption 3.iii

$$\frac{\mathbf{V}'\mathbf{M}_{hij}(\bar{\mathbf{e}}_{h\circ j}-\bar{\mathbf{e}}_{h\circ\circ})}{\sqrt{T-h}} \to_d N\left(0,\sigma_v^2\pi_{hj}\mathbf{I}_{h+1}\right). \tag{A.10}$$

Using (A.7), and (A.10) in (A.9), and noting that $M/(T-h)\to\kappa_2$, we obtain

$$M^{-1/2}\sum_{i=1}^{M}(\boldsymbol{\epsilon}_{ij}-\bar{\boldsymbol{\epsilon}}_{i\circ}) \to_d N\left[0,\kappa_2\frac{\pi_{hj}}{\sigma_v^2}\mathbf{I}_{h+1}\right].$$

This completes the proof. ■

Lemma A.2 *Let $\boldsymbol{\epsilon}_{ij}=\hat{\mathbf{b}}_{ij}-\mathbf{b}_{ij}$, and assume Assumptions 1-3 hold, where $\hat{\mathbf{b}}_{ij}$ is the LS estimator of $(h+1)\times 1$ vector $\mathbf{b}_{ij}=(b_{ij0},b_{ij1},...,b_{ijh})'$ in the DL regression (2). In addition, let $M,N,T\to_j\infty$ such that $M/T\to\kappa_1$ and $N/T\to\kappa_2$, for some $0\le\kappa_1,\kappa_2<\infty$. Then,*

$$N^{-1}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}=O_p\left(T^{1/2}\right), \tag{A.11}$$

and

$$M^{-1}\sum_{i=1}^{M}\left(\boldsymbol{\epsilon}_{ij}-N^{-1}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}\right)=O_p\left(T^{1/2}\right). \tag{A.12}$$

Proof. Multiplying (A.6) by $N^{-1/2}$, we obtain

$$N^{-1}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}=\left(\frac{\mathbf{V}'\mathbf{M}_{hij}\mathbf{V}}{T-h}\right)^{-1}\left(\frac{1}{T-h}\right)^{1/2}\frac{\mathbf{V}'\mathbf{M}_{hij}\bar{\mathbf{e}}_{hi\circ}}{\sqrt{T-h}},$$

where $\mathbf{V}'\mathbf{M}_{hij}\bar{\mathbf{e}}_{hi\circ}/\sqrt{T-h}=O_p(1)$ by Assumption 3.ii, and $[\mathbf{V}'\mathbf{M}\mathbf{V}/(T-h)]^{-1}=O_p(1)$ is implied by Assumption 3.i, since $\sigma_v^2\mathbf{I}_{h+1}$ is nonsingular. Noting that h is fixed, result (A.11) follows.

Similarly, we obtain

$$M^{-1}\sum_{i=1}^{M}\left(\boldsymbol{\epsilon}_{ij}-N^{-1}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}\right)=\left(\frac{\mathbf{V}'\mathbf{M}_{hij}\mathbf{V}}{T-h}\right)^{-1}\left(\frac{1}{T-h}\right)^{1/2}\frac{\mathbf{V}'\mathbf{M}\left(\bar{\mathbf{e}}_{h\circ j}-\bar{\mathbf{e}}_{h\circ\circ}\right)}{\sqrt{T-h}}.$$

Using the conditions i and ii of Assumption 3, it follows that $M^{-1}\sum_{i=1}^{M}\left(\boldsymbol{\epsilon}_{ij}-N^{-1}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}\right)=O_p\left(T^{1/2}\right)$, as required. ■

Proof of Theorem 1. We establish asymptotic distribution starting with the case where $(M,N,T)\to\infty$ jointly such that $N/T\to 0$ and $M/T\to 0$, first. Let $\boldsymbol{\epsilon}_{ij}=\hat{\mathbf{b}}_{ij}-\mathbf{b}_{ij}$. We have

$$\hat{\mathbf{b}}_i=N^{-1}\sum_{j=1}^{N}\hat{\mathbf{b}}_{ij}=N^{-1}\sum_{j=1}^{N}\mathbf{b}_{ij}+N^{-1}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}.$$

Substituting $\mathbf{b}_{ij}=\mathbf{b}_i+\mathbf{c}_j+\boldsymbol{\omega}_{ij}$ (Assumption 1), we obtain

$$\hat{\mathbf{b}}_i=\mathbf{b}_i+N^{-1}\sum_{j=1}^{N}\left(\mathbf{c}_j+\boldsymbol{\omega}_{ij}\right)+N^{-1}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}.$$

But $N^{-1}\sum_{j=1}^{N}\mathbf{c}_j=0$. Hence

$$\sqrt{N}\left(\hat{\mathbf{b}}_i-\mathbf{b}_i\right)=N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\omega}_{ij}+N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}. \tag{A.13}$$

Since $\boldsymbol{\omega}_{ij}\sim IID\left(\mathbf{0},\boldsymbol{\Omega}_{ij}\right)$, $K_0<\left\|\boldsymbol{\Omega}_{ij}\right\|<K_1$, under Assumption 1, we have

$$N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\omega}_{ij}\to_d N\left(0,\bar{\boldsymbol{\Omega}}_{i\circ}\right), \tag{A.14}$$

where $\bar{\boldsymbol{\Omega}}_{i\circ}=N^{-1}\sum_{j=1}^{N}\boldsymbol{\Omega}_{ij}$. In addition, result (A.11) of Lemma A.2 implies $N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}=O_p\left(N^{1/2}T^{-1/2}\right)$. Hence for any i, we obtain

$$\sqrt{N}\left(\hat{\mathbf{b}}_i-\mathbf{b}_i\right)\to_d N\left(0,\bar{\boldsymbol{\Omega}}_{i\circ}\right).$$

Consider the asymptotic distribution of $\hat{\mathbf{c}}_j$ next. We have

$$\begin{aligned}\sqrt{M}\left(\hat{\mathbf{c}}_j-\mathbf{c}_j\right) &= M^{-1/2}\sum_{i=1}^{M}\boldsymbol{\omega}_{ij}+M^{-1/2}\sum_{i=1}^{M}\boldsymbol{\epsilon}_{ij}-M^{-1/2}N^{-1}\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{\omega}_{ij} \\ &\quad -M^{-1/2}N^{-1}\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}. \qquad (A.15)\end{aligned}$$

Using the same arguments as before, we have

$$M^{-1/2}\sum_{i=1}^{M}\boldsymbol{\omega}_{ij}\rightarrow_d N\left(\mathbf{0},\bar{\boldsymbol{\Omega}}_{\circ j}\right), \qquad (A.16)$$

and

$$M^{-1/2}N^{-1}\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{\omega}_{ij}=O_p\left(N^{-1/2}\right), \qquad (A.17)$$

where $\bar{\boldsymbol{\Omega}}_{\circ j}=M^{-1}\sum_{i=1}^{M}\boldsymbol{\Omega}_{ij}$. Using result (A.12) of Lemma A.2, we obtain

$$M^{-1/2}\sum_{i=1}^{M}\boldsymbol{\epsilon}_{ij}=O_p\left(M^{1/2}T^{-1/2}\right),$$

and

$$M^{-1/2}N^{-1}\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}=O_p\left(M^{1/2}T^{-1/2}\right).$$

Hence, for any j,

$$\sqrt{M}\left(\hat{\mathbf{c}}_j-\mathbf{c}_j\right)\rightarrow_d N\left(\mathbf{0},\bar{\boldsymbol{\Omega}}_{\circ j}\right).$$

We establish asymptotic distribution when $(M,N,T)\rightarrow\infty$ jointly such that $N/T\rightarrow\kappa_1$ and $M/T\rightarrow\kappa_2$, for some $0<\kappa_1,\kappa_2<\infty$, next. Lemma A.1 establishes

$$N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\epsilon}_{ij}\rightarrow_d N\left(0,\kappa_1\boldsymbol{\Upsilon}_{i\circ}\right).$$

Using this result in (A.13), together with (A.14), yields

$$\sqrt{N}\left(\hat{\mathbf{b}}_i-\mathbf{b}_i\right)\rightarrow_d N\left(0,\bar{\boldsymbol{\Omega}}_{i\circ}+\kappa_1\boldsymbol{\Upsilon}_{i\circ}\right),$$

as desired. Finally, we establish the distribution of $\hat{\mathbf{c}}_j$. Consider the individual elements on the right side of (A.15). Result (A.17) continues to hold regardless of T being large relative to M or not. Hence,

$$\sqrt{M}\left(\hat{\mathbf{c}}_j - \mathbf{c}_j\right) \sim_d M^{-1/2}\sum_{i=1}^{M}\boldsymbol{\omega}_{ij} + M^{-1/2}\sum_{i=1}^{M}\left(\boldsymbol{\epsilon}_{ij} - \bar{\boldsymbol{\epsilon}}_{i\circ}\right).$$

Result (A.16) also continues to hold regardless of T being large relative to M or not. Using (A.16) and result (A.2) of Lemma A.1, we have

$$\sqrt{M}\left(\hat{\mathbf{c}}_j - \mathbf{c}_j\right) \to_d N\left(0, \bar{\boldsymbol{\Omega}}_{\circ j} + \kappa_2 \boldsymbol{\Upsilon}_{2,j}\right)$$

This completes the proof. ■

Proof of Proposition 1.. Proof of Proposition 1 follows the same lines of arguments as the proof of Theorem 1. Similarly to Lemma A.2 we have $\hat{\mathbf{b}}_j = \mathbf{b}_j + \boldsymbol{\epsilon}_j = \mathbf{b}_j + O_p\left(T^{-1/2}\right)$, and

$$\hat{\mathbf{b}} = N^{-1}\sum_{j=1}^{N}\hat{\mathbf{b}}_j = N^{-1}\sum_{j=1}^{N}\mathbf{b}_j + O_p\left(T^{-1}\right) = \mathbf{b} + N^{-1}\sum_{j=1}^{N}\boldsymbol{\omega}_j + O_p\left(T^{-1/2}\right),$$

where we substituted $\mathbf{b}_j = \mathbf{b} + \boldsymbol{\omega}_j$ (Assumption 4). Hence

$$\sqrt{N}\left(\hat{\mathbf{b}} - \mathbf{b}\right) = N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\omega}_j + O_p\left(N^{1/2}T^{-1/2}\right).$$

But since $\boldsymbol{\omega}_j \sim IID\left(\mathbf{0}, \boldsymbol{\Omega}\right)$, under Assumption 4, we have $N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\omega}_j \to_d N\left(\mathbf{0}, \boldsymbol{\Omega}\right)$. Therefore as $N, T \to_j \infty$ such that $N/T \to 0$, we obtain

$$\sqrt{N}\left(\hat{\mathbf{b}} - \mathbf{b}\right) \to_d N\left(\mathbf{0}, \boldsymbol{\Omega}\right).$$

Consider next the distribution under asymptotics $N, T \to_j \infty$ such that $N/T \to \kappa$ for some $0 < \kappa < \infty$. We have

$$\sqrt{N}\left(\hat{\mathbf{b}} - \mathbf{b}\right) = N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\omega}_{ij} + N^{-1/2}\sum_{j=1}^{N}\boldsymbol{\epsilon}_i,$$

where (using similar arguments as in the proof of Lemma A.1)

$$N^{-1/2} \sum_{j=1}^{N} \boldsymbol{\epsilon}_i \rightarrow_d N \left(0, \kappa \boldsymbol{\Upsilon}\right),$$

in which

$$\boldsymbol{\Upsilon} = \frac{\varkappa_h}{\sigma_v^2} \mathbf{I}_{h+1}, \tag{A.18}$$

$\sigma_v^2 = E\left(v_t^2\right)$, and $\varkappa_h$ is given by Assumption 5.ii. This completes the proof. ∎

A.2 Additional Empirical Results

Table A1: Estimates of IRF location effects ($c^{\delta}_{j,h}$) for oil price shocks cumulative multipliers at horizon $h = 4$

	City or Metro Area, State	$\hat{c}^{\delta}_{j,4}$	Conf. Interval$^{\lozenge}$
1	Amarillo, TX	-0.003	[-0.040,0.034]
2	Atlanta, GA	0.000	[-0.036,0.036]
3	Cedar Rapids, IA	-0.027	[-0.062,0.008]
4	Charlotte-Gastonia-Rock Hill, NC-SC	0.020	[-0.020,0.060]
5	Chattanooga, TN-GA	-0.013	[-0.044,0.018]
6	Cleveland-Akron, OH	-0.034	[-0.072,0.003]
7	Colorado Springs, CO	0.009	[-0.029,0.046]
8	Columbia, MO	0.012	[-0.022,0.046]
9	Columbia, SC	0.004	[-0.035,0.043]
10	Dallas-Fort Worth, TX	-0.013	[-0.051,0.024]
11	Denver-Boulder-Greeley, CO	-0.011	[-0.045,0.023]
12	Dover, DE	0.026	[-0.017,0.068]
13	Houston-Galveston-Brazoria, TX	0.009	[-0.023,0.041]
14	Huntsville, AL	0.033	[-0.001,0.066]
15	Jonesboro, AR	-0.016	[-0.050,0.018]
16	Joplin, MO	0.001	[-0.037,0.039]
17	Knoxville, TN	0.008	[-0.027,0.044]
18	Lexington, KY	0.014	[-0.025,0.054]
19	Los Angeles-Riverside-Orange County, CA	0.009	[-0.027,0.046]
20	Louisville, KY-IN	0.015	[-0.023,0.052]
21	Lubbock, TX	-0.003	[-0.038,0.031]
22	Memphis, TN-AR-MS	0.008	[-0.044,0.061]
23	Montgomery, AL	-0.016	[-0.052,0.021]
24	Odessa-Midland, TX	0.000	[-0.029,0.029]
25	Oklahoma City, OK	0.032	[-0.012,0.077]
26	Omaha, NE-IA	-0.018	[-0.044,0.009]
27	Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	0.010	[-0.027,0.048]
28	Phoenix-Mesa, AZ	0.019	[-0.020,0.058]
29	Portland-Salem, OR-WA	-0.069*	[-0.117,-0.020]
30	Raleigh-Durham-Chapel Hill, NC	-0.014	[-0.051,0.024]
31	Reno, NV	0.021	[-0.027,0.069]
32	Salt Lake City-Ogden, UT	0.000	[-0.044,0.044]
33	San Antonio, TX	0.014	[-0.030,0.059]
34	South Bend, IN	-0.028	[-0.065,0.009]
35	Springfield, IL	-0.004	[-0.050,0.042]
36	St. Cloud, MN	0.021	[-0.013,0.055]
37	St. Louis, MO-IL	-0.035	[-0.082,0.013]
38	Tacoma, WA	-0.010	[-0.057,0.036]
39	Tucson, AZ	0.011	[-0.030,0.053]
40	Waco, TX	0.010	[-0.033,0.053]
41	York, PA	0.007	[-0.023,0.036]

Notes: ($\lozenge$) 95 percent family-wise confidence intervals are reported.
(*) Statistically significant estimates are highlighted by asterisk.
Cumulative location effects are defined as $c^{\delta}_{j,h} = \sum_{\ell=0}^{h} c_{jh}$, where c_{jh} are the location effects defined in Assumption 1. This table reports the MGDL cumulative location effects estimates $\hat{c}^{\delta}_{i,h} = \sum_{\ell=0}^{h} \hat{c}_{ih}$ at horizon $h = 4$ quarters for the crude oil price shocks. The MGDL estimates are based on regressions (17) augmented with seasonal dummies, where x_{ijt} is log-difference of price for product category i in city j in period t from C2ER dataset, which spans $M = 43$ reported categories over $N = 41$ cities, covering $T = 104$ quarterly periods from 1990Q1 to 2015Q4.

Table A2: Retail price effects of U.S. monetary policy Shocks: MGDL estimates of cumulative multipliers at horizon $h = 4$

	U.S. MP shock:	BRW		AD		RR		NS		GSS	
	Product category	$\hat{\delta}_{i,4}$	Conf. Int.$^{\lozenge}$	$\hat{\delta}_{i,4}$	Conf. Int.$^{\lozenge}$	$\hat{\delta}_{i,4}$	Conf. Int.$^{\lozenge}$	$\hat{\delta}_{i,4}$	Conf. Int.$^{\lozenge}$	$\hat{\delta}_{i,4}$	Conf. Int.$^{\lozenge}$
1	TBONESTEAK	0.033	[-0.336,0.401]	-0.058	[-0.326,0.210]	-0.016	[-0.077,0.045]	0.203	[-0.272,0.678]	0.359	[-0.038,0.756]
2	GROUNDBEEF	0.227	[-0.238,0.691]	-0.136	[-0.467,0.194]	-0.029	[-0.108,0.050]	0.211	[-0.426,0.849]	0.470	[-0.047,0.987]
3	FRYINGCHICKEN	0.041	[-0.312,0.394]	-0.070	[-0.334,0.195]	0.000	[-0.067,0.066]	-0.035	[-0.458,0.387]	0.011	[-0.362,0.385]
4	CANNED TUNA	0.047	[-0.438,0.532]	-0.182	[-0.511,0.147]	-0.001	[-0.081,0.079]	-0.176	[-0.799,0.446]	-0.178	[-0.720,0.364]
5	WHOLEMILK	-0.020	[-0.545,0.504]	-0.198	[-0.555,0.159]	-0.018	[-0.110,0.073]	0.219	[-0.491,0.928]	0.139	[-0.463,0.741]
6	EGGS	-0.072	[-1.276,1.132]	-0.189	[-0.939,0.561]	0.014	[-0.178,0.207]	0.009	[-1.503,1.520]	0.188	[-1.060,1.435]
7	MARGARINE	0.058	[-0.322,0.439]	-0.070	[-0.381,0.241]	-0.010	[-0.084,0.064]	-0.207	[-0.724,0.311]	-0.241	[-0.711,0.230]
8	CHEESE	0.028	[-0.309,0.365]	-0.038	[-0.241,0.165]	0.008	[-0.031,0.048]	-0.112	[-0.555,0.330]	-0.319	[-0.701,0.063]
9	POTATOES	0.676	[-0.340,1.693]	0.153	[-0.623,0.929]	0.000	[-0.209,0.209]	-0.114	[-1.568,1.341]	-0.179	[-1.410,1.052]
10	BANANAS	0.130	[-0.324,0.584]	0.150	[-0.377,0.677]	0.044	[-0.096,0.184]	0.067	[-0.499,0.633]	-0.202	[-0.712,0.309]
11	LETTUCE	0.183	[-1.337,1.703]	0.275	[-1.133,1.683]	0.013	[-0.359,0.386]	0.228	[-1.378,1.833]	-0.232	[-1.611,1.147]
12	BREAD	0.062	[-0.307,0.431]	-0.037	[-0.346,0.273]	0.016	[-0.050,0.083]	0.057	[-0.445,0.559]	-0.011	[-0.447,0.426]
13	COFFEE	0.127	[-0.407,0.661]	0.080	[-0.484,0.644]	0.064	[-0.083,0.212]	0.000	[-0.737,0.737]	-0.372	[-0.987,0.243]
14	SUGAR	-0.039	[-0.397,0.319]	0.107	[-0.165,0.380]	0.023	[-0.047,0.094]	-0.047	[-0.542,0.448]	-0.070	[-0.489,0.349]
15	CORNFLAKES	0.068	[-0.222,0.359]	0.027	[-0.248,0.302]	0.022	[-0.043,0.088]	0.016	[-0.384,0.415]	-0.033	[-0.382,0.317]
16	CANNED PEAS	0.023	[-0.444,0.490]	-0.138	[-0.500,0.223]	-0.018	[-0.103,0.066]	-0.179	[-0.786,0.428]	-0.257	[-0.769,0.254]
17	CANNED PEACHES	0.040	[-0.208,0.288]	0.014	[-0.132,0.160]	0.010	[-0.021,0.042]	-0.050	[-0.361,0.262]	-0.060	[-0.337,0.217]
18	TISSUES	0.279	[-0.213,0.771]	0.303	[-0.083,0.690]	0.056	[-0.045,0.157]	0.229	[-0.424,0.883]	0.215	[-0.313,0.743]
19	DETERGENT	0.022	[-0.627,0.672]	0.123	[-0.498,0.743]	-0.021	[-0.187,0.145]	-0.013	[-0.915,0.889]	0.483	[-0.261,1.227]
20	SHORTENING	0.284	[-0.225,0.793]	-0.126	[-0.411,0.159]	0.003	[-0.048,0.054]	0.358	[-0.394,1.110]	0.083	[-0.554,0.720]
21	FROZEN CORN	0.056	[-0.501,0.613]	0.203	[-0.238,0.644]	0.059	[-0.055,0.172]	0.016	[-0.391,0.423]	-0.027	[-0.392,0.338]
22	SOFT DRINK	0.046	[-0.242,0.333]	0.027	[-0.179,0.233]	0.005	[-0.042,0.052]	-0.009	[-0.383,0.365]	0.037	[-0.296,0.371]
23	HOME PRICE	0.022	[-0.086,0.130]	0.014	[-0.066,0.093]	0.002	[-0.017,0.020]	0.041	[-0.105,0.187]	-0.008	[-0.154,0.138]
24	PHONE	0.014	[-0.183,0.210]	0.016	[-0.124,0.156]	-0.013	[-0.046,0.019]	-0.070	[-0.305,0.166]	0.016	[-0.192,0.225]
25	AUTO MAINTENANCE	0.799	[-0.855,2.454]	-0.006	[-0.141,0.130]	0.000	[-0.031,0.030]	0.048	[-2.326,2.422]	0.243	[-1.753,2.239]
26	GASOLINE	-0.212	[-1.594,1.170]	0.167	[-0.660,0.994]	0.050	[-0.154,0.255]	0.811	[-1.090,2.713]	0.686	[-1.008,2.381]
27	DOCTOR VISIT	-0.024	[-0.213,0.165]	-0.012	[-0.175,0.152]	-0.004	[-0.042,0.034]	-0.083	[-0.328,0.163]	-0.071	[-0.293,0.151]
28	DENTIST VISIT	-0.215	[-0.668,0.239]	0.027	[-0.348,0.402]	-0.006	[-0.107,0.096]	-0.142	[-0.774,0.490]	0.011	[-0.528,0.550]
29	MCD.'S HAMBURGER	-0.018	[-0.204,0.167]	-0.029	[-0.140,0.082]	0.001	[-0.023,0.025]	-0.096	[-0.343,0.150]	-0.069	[-0.285,0.146]
30	PIZZA	0.165	[-0.112,0.442]	-0.054	[-0.177,0.069]	0.000	[-0.027,0.028]	-0.036	[-0.428,0.356]	-0.170	[-0.504,0.165]
31	FRIED CHICKEN	0.015	[-0.191,0.221]	-0.004	[-0.138,0.129]	0.009	[-0.019,0.038]	0.025	[-0.233,0.283]	-0.078	[-0.298,0.141]
32	HAIRCUT	0.042	[-0.109,0.192]	0.014	[-0.114,0.143]	0.003	[-0.025,0.031]	0.037	[-0.139,0.213]	0.017	[-0.149,0.184]
33	BEAUTY SALON	-0.019	[-0.220,0.182]	0.064	[-0.132,0.260]	0.012	[-0.031,0.055]	0.002	[-0.270,0.274]	-0.032	[-0.284,0.220]
34	TOOTHPASTE	-0.014	[-0.355,0.327]	-0.016	[-0.214,0.182]	-0.005	[-0.051,0.041]	-0.009	[-0.488,0.471]	-0.096	[-0.497,0.305]
35	DRY CLEANING	0.003	[-0.141,0.147]	-0.014	[-0.115,0.087]	-0.002	[-0.025,0.022]	-0.025	[-0.220,0.170]	-0.014	[-0.187,0.160]
36	MAN'S SHIRT	0.060	[-0.361,0.482]	0.138	[-0.279,0.556]	0.029	[-0.072,0.130]	0.019	[-0.517,0.555]	0.016	[-0.452,0.484]
37	APPLIANCE REPAIR	0.031	[-0.187,0.249]	-0.043	[-0.199,0.114]	-0.008	[-0.043,0.027]	-0.004	[-0.282,0.274]	-0.042	[-0.308,0.224]
38	NEWSPAPER	-0.126	[-0.403,0.151]	-0.013	[-0.166,0.141]	-0.003	[-0.039,0.033]	-0.104	[-0.419,0.212]	-0.055	[-0.331,0.221]
39	MOVIE	-0.015	[-0.124,0.094]	-0.009	[-0.110,0.092]	0.000	[-0.024,0.024]	-0.029	[-0.173,0.115]	-0.052	[-0.184,0.081]
40	BOWLING	0.035	[-0.177,0.246]	-0.056	[-0.236,0.124]	-0.008	[-0.051,0.034]	0.033	[-0.238,0.303]	-0.068	[-0.297,0.161]
41	TENNIS BALLS	-0.020	[-0.293,0.253]	-0.019	[-0.209,0.171]	-0.003	[-0.048,0.042]	-0.013	[-0.345,0.319]	-0.049	[-0.341,0.242]
42	BEER	0.201	[-0.343,0.746]	0.040	[-0.438,0.519]	-0.017	[-0.141,0.108]	0.241	[-0.477,0.958]	-0.037	[-0.666,0.593]
43	WINE	-0.033	[-0.287,0.222]	-0.059	[-0.406,0.288]	-0.003	[-0.092,0.085]	-0.008	[-0.320,0.303]	-0.037	[-0.324,0.249]

Notes: ($\lozenge$) 95 percent family-wise confidence intervals are reported.

(*) None of the estimates in this table are statistically significant base don the reported family-wise confidence intervals.

This table reports the MGDL cumulative multiplier estimates $\hat{\delta}_{i,h}$ at horizon $h = 4$ quarters for the U.S. monetary policy shocks by Bu, Rogers, and Wu (2021, BRW), Aruoba and Drechsel (2022, AD), Romer and Romer (2004, RR) updated by Wieland (2021), Nakamura and Steinsson (2018, NS), and Gürkaynak, Sack, and Swanson (2005, GSS). The MGDL estimates are based on augmented DL regressions $x_{ijt} = a_{ij} + \sum_{\ell=0}^{h} b_{ij\ell} v_{t-\ell} + \varphi_1 x_{i,j,t-h-1} + +e_{hit}$, where x_{ijt} is log-difference of price for product category i in city j in period t from C2ER dataset, which spans $M = 43$ reported categories over $N = 41$ cities, covering $T = 104$ quarterly periods from 1990Q1 to 2015Q4.