Distributional—Aggregate Feedback in the Macroeconomic Effects of National Minimum Wage Shocks*

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March 7, 2026

Abstract

This paper estimates the distributional and macroeconomic effects of minimum wage shocks in Korea using a functional vector autoregression (fVAR) model. I find that a positive minimum wage shock reduces household income and the employment rates of household heads, with the most pronounced declines at the bottom of the distribution. Because the income contraction driven by severe job losses is disproportionately concentrated among vulnerable households, relative inequality worsens, leading to a significant increase in the Gini index. Departing from the existing fVAR literature, I demonstrate that incorporating cross-sectional information is quantitatively crucial for estimating aggregate effects. Specifically, the negative aggregate employment response is primarily driven by the endogenous responses of low-income households; ignoring these distributional feedbacks within a standard VAR framework renders the aggregate employment decline statistically insignificant and masks the true inflationary pressures. These findings suggest that the minimum wage may be an inefficient policy tool for correcting labor market frictions.

JEL Classification: J38, C31, E32
Keywords: Minimum Wages, Income Distribution, Functional Vector Autoregressions

*This paper is a substantially revised version of "The Impact of Minimum Wage on Household Income Distribution"(with Sungjoon Kwon and Hwanoong Lee) of the Korea Institute of Public Finance, Kwon et al. (2025).

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1 Introduction

Minimum wage policy is one of the most prominent and contentious labor market policies worldwide. Although legal objectives of the policy differ across countries, academic and policy debates have largely focused on two dimensions—efficiency and inequality—which are not independent.[1] While standard competitive market models predict that higher minimum wages increase involuntary unemployment, models of monopsony power they can generate efficiency gains. In such settings, aggregate efficiency depends on distributional effects: raising the purchasing power of low-income workers may boost aggregate economy more. From a distributional perspective, the benefits of minimum wages for low-income workers hinge on both aggregate and distributional employment responses. These considerations underscore the need to jointly analyze the aggregate and distributional effects of minimum wages. Yet, many empirical studies consider these dimensions independently, abstracting from their interactions and general equilibrium feedbacks.

I estimate the distributional and aggregate impulse responses to minimum wage shocks in Korea using a functional vector autoregressive (fVAR) model. To identify the structural shocks, I treat the Kaitz index, a measure of minimum wage intensity, as the most endogenous macroeconomic variable. Following the standard fVAR literature, distributional factors are ordered as more endogenous than the macroeconomic aggregates. To the best of my knowledge, this is the first study to employ an fVAR framework to simultaneously analyze both the macroeconomic and distributional effects of minimum wage shocks.

I focus on the case of Korea for two primary reasons. First, similar to the United Kingdom, South Korea implements a nationwide minimum wage policy, making it an ideal setting to estimate the *national-level* macroeconomic effects using an fVAR model. In such contexts, many micro-econometric studies exploit regional variations in the policy's exposure or intensity to identify minimum wage shocks. While these approaches facilitate rigorous causal

[1] For example, Berger et al. (2025) notes that the U.S. Treasury emphasizes both efficiency and redistribution in supporting minimum wages, whereas South Korea, the focus of this paper, primarily frames minimum wage policy in redistributive terms. See Article 1 of Korea's Minimum Wage Act.

inference, they ultimately measure the relative differences between regions rather than the aggregate effect, as discussed by Nakamura and Steinsson (2014) and Matthes et al. (2025).[2] Second, there exists a novel dataset in Korea that provides repeated cross-sectional household income and labor-force status at a quarterly frequency. Because of this high-frequency data, we can estimate dynamic causal effects at business cycle frequencies. Given the strong policy interest in the effects of minimum wages, the Korean case provides a valuable setting for studying their aggregate and distributional impacts.

The main results are as follows. First, I find that a positive minimum wage shock reduces household income across all income levels. More importantly, it reduces the income of low-income households more severely than that of high-income households. Second, while the shock significantly reduces aggregate employment in the benchmark model, this contractionary effect becomes statistically insignificant in a restricted model that entirely excludes the cross-sectional income distribution. In addition, through a counterfactual exercise, I show that the decline in aggregate employment is primarily driven by the responses of lower-income households; shutting down their endogenous responses dampens the aggregate employment decline by approximately $9.54 \sim 10.27\%$. This highlights the crucial role of feedback between macroeconomic aggregates and cross-sectional distributions. Lastly, the employment rates of household heads decrease across all income groups. Similar to the distributional income responses, this effect is more pronounced for lower-income households. The main results hold regardless of the assumed exogeneity order of minimum wage shocks among macroeconomic variables.

These findings contribute to the literature in two main ways. First, using a tractable fVAR framework, this paper demonstrates that the macroeconomic and distributional effects of minimum wage shocks are inextricably linked. By exploiting a novel micro-dataset, I empirically capture the general equilibrium spillovers typically analyzed in heterogeneous-

[2] Intuitively, estimates based on regional variation capture the localized employment response when one region is relatively more exposed to a minimum wage increase than the national average. However, from a macroeconomic perspective, we are often more interested in the aggregate question: "how much does national employment change when the country raises the national minimum wage?"

agent structural models, but with a significantly lower computational burden. Specifically, I document a crucial transmission channel: minimum wage hikes induce disproportionate job losses among low-income households, which subsequently disqualifies them from in-work benefits such as the Earned Income Tax Credit (EITC) or Child Tax Credit (CTC). This mechanism amplifies their income contraction and significantly worsens overall inequality (Gini index), suggesting that the minimum wage may be an inefficient tool for correcting wage markdowns in oligopsonistic labor markets, a conclusion that aligns with the structural insights of Hurst et al. (Forthcoming).

Second, this paper highlights the critical necessity of incorporating cross-sectional information to explain aggregate macroeconomic responses. While previous fVAR studies (e.g., Chang and Schorfheide (2025), Chang et al. (2024)) concluded that cross-sectional distributions are not quantitatively important for aggregate dynamics, they prove to be crucial in this context. Through counterfactual exercises, I show that muting the endogenous responses of the bottom deciles significantly dampens the aggregate employment decline. Furthermore, estimating a standard VAR that explicitly omits distributional factors renders the negative aggregate employment effect statistically insignificant and alters the inflationary implications. This underscores that the ability of fVAR models to capture micro-macro spillovers depends heavily on the specific shocks and variables examined, highlighting its immense value in evaluating redistributive labor market policies.

Related Literature There exists a voluminous literature estimating the employment effects of minimum wages using traditional microeconometric and time-series reduced-form models. Building on this foundation, this paper directly relates to two specific strands: 1) evaluating the impacts of nationwide minimum wage policies, and 2) analyzing the dynamic interplay between aggregate and distributional effects within VAR frameworks.

First, evaluating a nationwide minimum wage poses unique identification challenges, as it precludes the use of standard state-level policy variations. A growing strand of microeconometric literature tackles this by exploiting regional exposure or rich administrative data. For instance, Giupponi et al. (2024) exploit geographical variation in wage levels to assess the UK's national minimum wage, showing substantial income gains up to the middle of the distribution. Similarly, Kim et al. (2023) investigate the employment margins of a nationwide minimum wage policy, highlighting unintended micro-level adjustments such as strategic hours reductions. While these microeconometric studies provide rich granular insights into firm and worker adjustment margins, they often abstract from general equilibrium macro-dynamics and aggregate spillovers.

Second, to capture these aggregate macroeconomic dynamics, some studies employ time-series approaches. For example, Herzog-Stein and Logeay (2019) utilize a VAR framework to evaluate the short-term macroeconomic impacts of introducing a statutory nationwide minimum wage. Furthermore, structural macro-labor studies, such as Berger et al. (2025) and Hurst et al. (Forthcoming), explore the aggregate efficiency and welfare implications of minimum wages in frictional labor markets. However, standard VAR models are inherently limited in their ability to integrate the rich cross-sectional heterogeneity highlighted by the microeconometric literature.

Finally, this paper bridges these gaps using the functional VAR (fVAR) methodology developed by Chang et al. (2022), Chang et al. (2024), Chang et al. (2025), Ettmeier (2024) and Kang and Lee (2026). In particular, Chang et al. (2024) and Chang and Schorfheide (2025) estimate state-space fVAR models to study the dynamics of technology and monetary policy shocks, respectively. A key conclusion from these previous studies is that the spillovers between aggregate and cross-sectional distributional dynamics are generally small and quantitatively unimportant. Departing from this conclusion, this paper demonstrates that for minimum wage shocks, incorporating cross-sectional information is quantitatively crucial for estimating aggregate employment effects, thereby expanding the empirical applicability of the fVAR methodology.

Section 2 explains the minimum wage policy in Korea briefly, data that this paper uses, empirical methodologies and identification assumption. Section 3 present main results of fVAR model. Section 4 concludes the paper.

2 Empirical Analysis

In this section, I briefly introduce the background of minimum wage policy in Korea in Section 2.1. And in Section 2.2, I explain the data that this paper uses. Section 2.3 explains the empirical framework of the fVAR model and Section 2.4 discusses the identification assumption.

2.1 Institutional Background: Minimum wage policy in Korea

Minimum Wage Act in Korea states the purpose of the minimum wage in Article 1 as follows: The purpose of this Act is to stabilize workers' lives and to improve the quality of the labor force by guaranteeing a certain minimum level of wages to workers, thereby contributing to the sound development of the national economy.[3] The Ministry of Employment and Labor is mandated to determine and announce the minimum wage for the subsequent year by August 15. It is determined by the Minimum Wage Commission (MWC), which consists of 27 members: 9 representing workers, 9 representing employers, and 9 representing public interest. The final determination requires a majority vote, necessitating approval from at least 14 commissioners. In addition, the MWC reports the official affected rate of the minimum wage, the share of workers who will have higher wages due to minimum wage increases, and the share of workers who have wages lower than the minimum wage in the current year.[4]

Practically, the policy was implemented from 1988. At its inception in 1988, the minimum wage system was initially mandated solely for manufacturing firms employing 10 or more reg-

[3] See the full legal statements from the following link: https://elaw.klri.re.kr/kor_service/lawView.do?hseq=19125&lang=

[4] The official website in English is as follows: https://www.minimumwage.go.kr/english/introduce/commission.do. The website in Korean reports the related statistics. However, unfortunately, the website in English does not report them. Thus, for more details, please visit https://www.minimumwage.go.kr/minWage/about/main.do and translate it using appropriate services.

ular workers. The system applied a two-tier wage structure based on industry groups. Group 1 (low-wage sector) encompassed 12 industries: food products, textiles, apparel, leather, footwear, wood and cork, paper products, rubber, plastic products, ceramics, electrical machinery, and miscellaneous manufacturing. Group 2 consisted of 16 industries, including beverages, tobacco, furniture, printing and publishing, industrial chemicals, petroleum refining, glass products, basic metals (iron, steel, and non-ferrous), fabricated metal products, machinery, transport equipment, and precision instruments.

Following its initial implementation, the scope of coverage was progressively expanded. Mining and construction were added in July 1988, and by July 1989, the policy was extended to cover all industries. The threshold for firm size was also gradually lowered. Originally set at 10 or more regular employees, the requirement was relaxed to 5 or more in 1999. Effective November 24, 2000, the Minimum Wage Act became applicable to all workplaces with at least one employee, thereby achieving universal coverage.

Figure 1 presents the trend of minimum wage with growth rate in Korea from 1990 to 2026. In addition, from 1988, the minimum wages were set at 462.5 KRW per hour for Group 1 and 487.5 KRW per hour for Group 2. Starting in 1989, this dual-track system was abolished in favor of a unified national rate of 600 KRW per hour, followed by consistent increases in subsequent years.

2.2 Data

This paper uses both macroeconomic time-series and repeated cross-sectional data to estimate the fVAR model. Section 2.2.1 and Section 2.2.2 introduces macroeconomic time-series data and cross-sectional data, respectively.

2.2.1 Macro Data

I use three types of macroeconomic variables − employment rate, inflation rate from consumer price index (CPI) and Kaitz index (=minimum wages/average wages) − in the fVAR

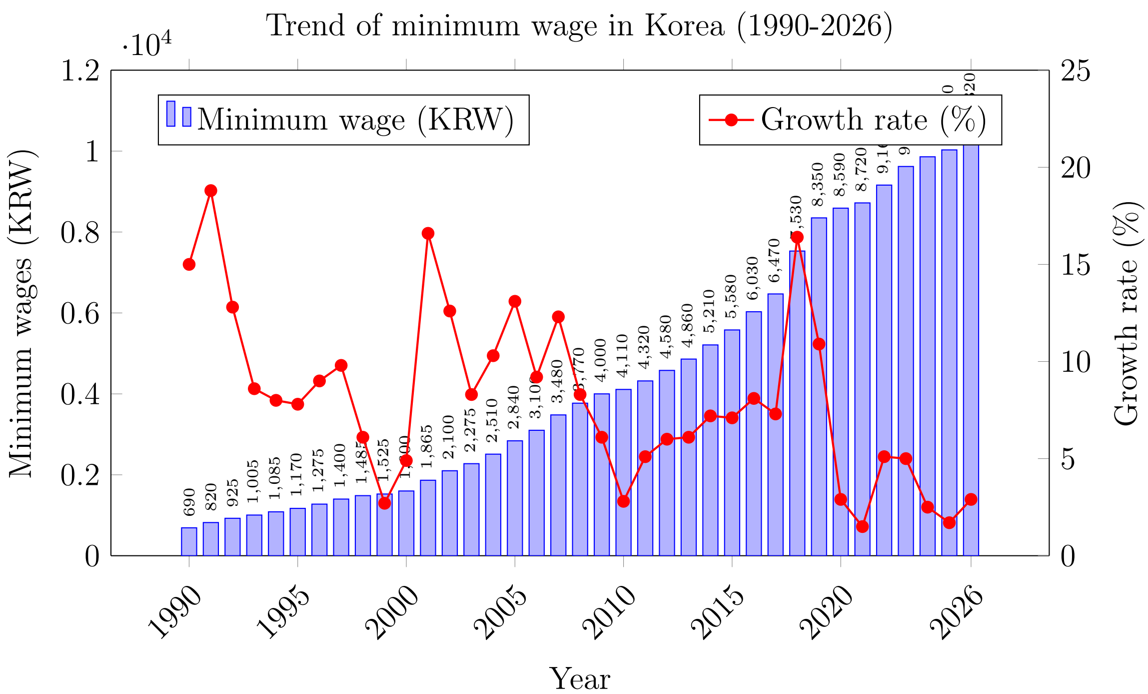


Figure 1: Trend of minimum wage in Korea (1990-2026).
Source: https://www.minimumwage.go.kr/minWage/policy/decisionMain.do (in Korean)

system. I use seasonally adjusted employment rate provided by the Ministry of Data and Statistics (MODS), and inflation rate calculated as quarter-on-quarter growth rate of CPI as CPI is seasonally adjusted. Seasonally adjusted employment rate and CPI are provided by the Ministry of Data and Statistics (MODS) in Korea. I will explain how I construct the Kaitz index in details later.[5]

The reasons why I use two additional macroeconomic variables as employment rate and inflation rate are as follows. First, because this paper considers minimum wage policy which directly affects labor market, I consider aggregate employment rather than gross domestic product (GDP). Additionally, even though the Korean population did not vary drastically during the sample period 2000Q1 − 2016Q4, this paper focuses on employment rate instead of the number of employees. Furthermore, studying labor market dynamics makes more consistent with other literature to study effects of minimum wages. Second, this paper also

[5]All the macroeconomic data used in this paper can be found from the Korean Statistical Information Service (KOSIS). Website: https://kosis.kr/eng/

investigates inflation. I argue that the inflation measured by CPI allows us to explore effects of minimum wages on production costs and purchasing power. Because higher minimum wages change marginal costs, it would increase product price. In addition, if higher minimum wages do not change aggregate employment significantly, it improves the purchasing power of low income households and raises price level.[6] Thus, it would be crucial to study the interaction between inflation and aggregate dynamics in exploring effects of minimum wage shocks.

Employment rate: Economically Active Population Survey (EAPS) This paper considers the quarterly and seasonally adjusted employment rate of EAPS conducted by the Ministry of Data and Statistics (MODS) in Korea from 2000 Q1 to 2016 Q4. The MODS produces EAPS which is the representative Korean labor market data for each month like the Current Population Survey (CPS) in the United States. The survey targets permanent residents aged 15 and older in sampled households nationwide. It explicitly excludes active-duty soldiers (including career soldiers and full-time reservists)[7], social service personnel, individuals residing abroad for work or study, inmates with confirmed sentences, and residents of sanitariums or prayer houses. The survey reference period is the week (seven days) containing the 15th of each month; however, if this week includes three or more consecutive public holidays, the reference period is shifted to the preceding week. The survey is conducted in 36,000 households across the country.

Kaitz index: Survey on Labor Conditions at Establishment (SLCE) With the same sample period, I construct the Kaitz index as follows:

$$K_t = \frac{MW_t}{AW_t} \tag{1}$$

where MW_t is a minium wage at time t and AW_t is an average hourly wage at time t. To measure the average hourly wage, I use the average total labor earnings and hours work from

[6] Of course it would not be one-to-one relationship in the presence of markup (producer market power) and markdown (firm labor market power).

[7] Note that most of Korean male aged 18 and older is mandated to serve military services.

the SLCE, produced by the Ministry of Employment and Labor (MOLE) in Korea. Specifically, I use "*Actual labor condition at establishment (ALCE)*" of the SLCE. This dataset includes workdays (total, regular and temporal), hours work (regular in total, regular in actual, regular in extra, temporal), labor earnings (total, regular, temporal in KRW) and fixed salary.[8] The ALCE of the SLCE survey is conducted in around 13,000 workplaces, excluding public institutions, agriculture, forestry, fishing, household services, and international/foreign organizations. The SLCE conducted surveys all workplaces, that is, those with one or more employees, from 2011. To make the sample consistent, this paper considers workplaces more than five-employee from 2000 Q1 to 2016 Q4. Using this dataset, I calculate $AW_t = \text{Total Labor Earnings}_t/\text{Total Hours Work}_t$.[9]

The Kaitz index is usually used in the macroeconomeric literature to study effects of minimum wages. Since the weighted average of minimum wages over average wages from each industry would exacerbate endogeneity, I use the simple aggregate intensity − minimum wages over average hourly wages.[10] As shown in (1), it measures the intensity of minimum wages. From the institutional backgrounds, as in other countries, minimum wages are fixed for one-year. Because this paper is interested in analyzing macroeconomic and distributional effects of minimum wages in the business-cycle frequencies, it is necessary to construct a time-varying index.[11] Because I use the Kaitz index rather than minimum wage level itself, I assume that it is the most endogenous aggregate variable in the fVAR system.

Seasonality in the Kaitz index Unlike the employment rate and the consumer price index, there are no officially seasonally adjusted series for total hours worked and labor

[8] Another data in the SLCE is "*Employment*". It includes related information of the number of employee, vacancies, new hires and separations. Both of dataset covers all industry except agriculture, forestry, fishing, household services, and international/foreign organizations. In addition, the *Employment* of SLCE is conducted in around 50,000 workplaces.

[9] There is no official data to be seasonally adjusted, unlike the case of employment rate, both labor earnings and hours work are seasonally adjusted using X-12 ARIMA.

[10] See Card and Krueger (1995) and Dolado et al. (2014) for related discussions. In addition, I use average hourly wage instead of median as there is no cross-sectional hourly wage data in Korea.

[11] It is natural to concern that the Kaitz index would exhibit seasonality, as the intensity of minimum wages would be weaken from the first quarter to the last quarter of the year. Because of this issue, I also estimate the fVAR with the Kaitz index with seasonally adjusted and results were almost the same.

earnings provided by the MOEL. Because the raw data for hours worked and earnings exhibit strong seasonality, I seasonally adjust these two series separately using the U.S. Census Bureau's X-13ARIMA-SEATS program. I then use these adjusted series to compute the average hourly wage and, subsequently, the Kaitz index.

A methodological issue arises here: while the constructed average hourly wage is free of seasonality, the resulting Kaitz index still exhibits a seasonality. One alternative would be to seasonally adjust the Kaitz index directly. However, this approach is problematic because it could smooth out the true policy variation—the structural innovations stemming from institutional minimum wage hikes, which typically occur at the beginning of the year. Furthermore, since the underlying sources of seasonality differ fundamentally between labor market variables and policy variables, directly adjusting the ratio is not ideal. Therefore, to appropriately address the residual seasonality without distorting the structural policy shocks, I estimate the fVAR model with quarterly dummy variables as exogenous controls.[12]

2.2.2 Repeated cross-sectional data

Income distribution: Household Income and Expenditure Survey In this paper, I consider the cross-sectional distribution of current income, which is the sum of labor income, business income, financial income and transfer income, and average employment rate over income level in this paper. To the end, I use the Household Income and Expenditure Survey (HIES), produced by the MODS in Korea.[13] The survey is conducted in around 7,200 households and it includes information related to income and expenditures in detail. It provides the labor force status but does not include hours work. This is why the paper employs hourly wages from other dataset, the SLCE.

This paper considers samples as 1) household heads aged between 25 and 64[14] 2) samples

[12]The indirect approach, implementing seasonal adjustments for denominator and numerator, is preferred approach in other cases either. See Lee (2018), Chapter 7: Seasonal Adjustment.

[13]The microdata can be downloaded from this MicroData Integrated Service (MDIS). Website: https://mdis.mods.go.kr/eng/index.do.

[14]Results are almost the same if we consider working age – from 25 to 55. I also check that main findings are robust for age group.

who report a positive number of household members, 3) reported current income and household expenditures − the sum of consumption and non-consumption expenditures − greater than or equal to 0. Furthermore, I exclude outlier from the data. That is, I drop the sample for the top and bottom 1%.

Because economy grows over time, the distributions of both nominal and real income shift over time, normally to the right. As in Chang and Schorfheide (2025), the current income in each quarter is normalized as follows. I first normalize the current income with the nominal gross domestic product (GDP) per capita for each quarter. For the case of labor income, we could multiply the average labor share as in Chang and Schorfheide (2025). And as in Chang and Schorfheide (2025), instead of taking a natural logarithm to the current income directly, I transform the current income z to x, which is the tangent hyperbolic of z as follows.

$$x = \frac{\log\left(\theta z + \sqrt{\theta z^2 + 1}\right)}{\theta} \tag{2}$$

with $\theta = 1$. Lastly, I transform the variable as kernel density for each period, with the upper and lower bounds as maximum and minimum values from all sample period, respectively. Figure 2 presents the histograms of each income for transformed and original for 1st quarter in 2000.

Lastly, I estimate the kernel density of the transformed current income for each quarter t as follows

$$\hat{f}_t(x) \;=\; \frac{1}{n_t h_t}\sum_{i=1}^{n_t} K\left(\frac{x - \tilde{x}_{it}}{h_t}\right), \tag{3}$$

where $K(\cdot)$ is a standard kernel and h_t is the data-driven bandwidth. We use Gaussian kernel and select bandwidth by Silverman's rule. Alternative kernels and bandwidths yield similar time-series patterns in $\{\hat{f}_t\}$. In this paper, I compute densities separately for current and labor income as needed. To compare the density consistent for each quarter, I estimate

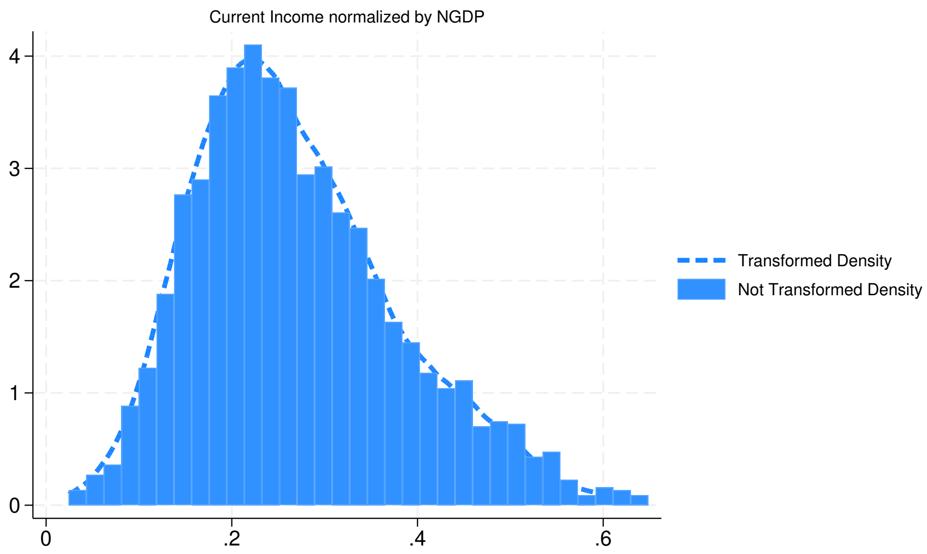


Figure 2: Histograms of Transformed & Original Current Income Distributions, Q1 2000. Dotted lines present the distributions of transformed current income from (2), bars present not transformed ones.

the above kernel density on a fixed support

$$\mathcal{X} = [0, x_{\max}], \qquad x_{\max} = \max_{i,t}\{\tilde{x}_{it}\},$$

so that the lower bound corresponds to zero income and the upper bound is the pooled-sample maximum observed over the whole sample period.[15]

Employment rate of Household-Head for Income Percentile: HIES Using the same HIES data, I also construct the cross-sectional distribution of the household-head employment rate. Specifically, for each period t, I partition the income distribution into N equally sized bins and compute the average employment rate of household heads within each bin.[16] In this paper, I set $N = 200$ to ensure that the income grid is sufficiently fine to

[15]For the kernel density estimation, I use the same method in Kang and Lee (2026).

[16]The HIES also provides labor force status of household members. Thus, we can compute employment rate of household for each of income quantile. However, because it is hard to interpret responses of it, this paper focuses on employment rate of household-head only.

capture nuanced employment responses across different income levels.[17]

2.3 Empirical method: Functional Vector Autoregression (fVAR) model

I explain the fVAR framework in this section. As shown in the previous literature, the fVAR model is similar with the standard VAR model. Thus, it is useful to consider the standard VAR framework first. When I estimate the fVAR model, I use the wild bootstrap

Standard Reduced-Form VAR Let Y_t be a $K \times 1$ vector of macroeconomic variables in each quarter t. In this paper, Y_t be a vector of employment rate, inflation and Kaitz index such that $Y_t = [\text{Emp}_t, \pi_t, \text{Kaitz}_t]$. Then, the standard reduced-form VAR(P) model is

$$Y_t = f(t) + \sum_{p=1}^{P} A_p Y_{t-p} + \gamma D_t + u_t \tag{4}$$

where $f(t) = \sum_{k=0}^{2} a_k t^k$ with $a_k \geq 0$ for all $k \in \{0, 1, 2\}$ is a polynomial of time, A_ps are coefficient matrix (3×3 matrix in this case), D_t presents a vector of deterministic exogenous variables and u_t is the vector of reduced-form residuals.

fVAR Model The fVAR model extends the standard VAR framework by incorporating functional variables—in this case, the cross-sectional income distribution.[18] The fundamental challenge is that a probability density function is a theoretically infinite-dimensional object, making its direct inclusion into a finite VAR system mathematically infeasible. To address this dimensionality problem, I apply Functional Principal Component Analysis (FPCA).

Formally, assuming the demeaned income density functions $f_t(x)$ are square-integrable, we can treat them as elements in a Hilbert space H equipped with an inner product $\langle f, g \rangle =$

[17] The empirical results are robust to the choice of N, provided it is sufficiently large. For instance, the baseline results remain virtually unchanged when using $N = 100$.

[18] The technical and mathematical details of the fVAR model and the functional principal component analysis (FPCA) procedure closely follow the framework in Kang and Lee (2026). For broader theoretical foundations regarding the consistency of fVAR estimation, see Chang et al. (2022) and Chang et al. (2025).

$\int f(r)g(r)dr$. Using FPCA, the infinite-dimensional density at time t can be efficiently approximated by truncating the basis expansion:

$$f_t(x) \approx \sum_{i=1}^{I} \xi_{i,t} v_i^*(x), \tag{5}$$

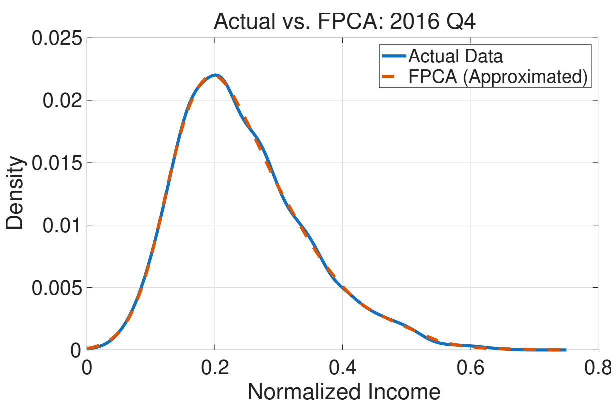
where $v_i^*(x)$ are the functional principal components (eigenfunctions) representing the orthogonal basis, and $\xi_{i,t} = \langle f_t, v_i^* \rangle$ are their corresponding time-varying scores. These scores concisely summarize the temporal variation in the cross-sectional distribution and can be directly incorporated into the VAR system as additional regressors.

The choice of the functional principal component basis over other functional bases is crucial for two methodological advantages. First, the FPCA basis minimizes the squared approximation error, meaning it approximates $f_t(x)$ most efficiently in the least-squares sense compared to any other I-dimensional basis. Second, and more importantly for the VAR estimation, the approximated components and the omitted (residual) components are orthogonal. This orthogonality ensures that truncating the infinite series into I finite factors does not introduce omitted-variable bias in finite samples. These two properties guarantee the general sample and bootstrap consistency of the fVAR procedure.

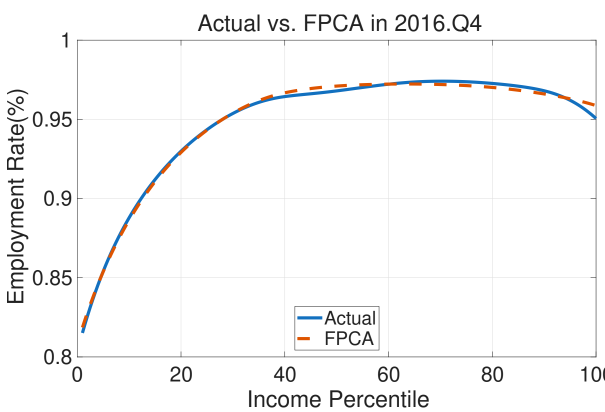
By extracting a finite set of scores, the theoretically infinite-dimensional density $\{\xi_t(i)\}_{i=1}^{\infty}$ is successfully transformed into a discrete, finite-dimensional vector $\{\xi_{i,t}\}_{i=1}^{I}$. Thus, defining the extended vector $Z_t = [Y_t', \xi_{1,t}, \ldots, \xi_{I,t}]'$, the fVAR is estimated analogously to a conventional VAR model:

$$Z_t = f(t) + \sum_{p=1}^{P} B_p Z_{t-p} + \Gamma D_t + u_t \tag{6}$$

Choice of Principal Components A key practical issue is determining the optimal truncation number, I^*. If I^* is too small, the estimated components fail to capture sufficient variation in the true density. Conversely, if I^* is too large, the estimation becomes unstable due to the limited length of the macroeconomic time series. Following standard practice, I choose the minimum number of factors I^* that explains at least 95% of the cumulative variation in the cross-sectional distribution. As a result, I set $I^* = 3$ for the baseline analysis, as these three principal components efficiently capture approximately 95.70% of the variation in the current income distribution. Figure 3a presents the original kernel density and the approximated density by the FPCA for the fourth quarter of 2016. In addition, I apply the same procedure to approximate the distribution of the household-head employment rate over income levels, where three factors ($I^* = 3$) explain roughly 97.05% of the variations (Figure 3b).



(a) Income density: Actual vs. FPCA



(b) Emp. rate over income: Actual vs. FPCA

Time trend, lags and quarterly dummy Lastly, I choose the degree of trend which maximizes log-likelihood, which implies a linear trend ($k = 1$), and the number of lag as one ($p = 1$) based on the Schwarz-Bayesian information criteria (SBC) in the benchmark model.[19] For each different model, I choose the degree of time trend and the number of lags with the same criteria.

It is worth to discuss that I consider exogenous quarterly dummy in the fVAR model (6). The Kaitz index exhibits seasonality even though I implement seasonal adjustments for hours-work and labor earnings. As discussed in Section 2.2.1, this paper does not implement seasonal adjustments for the Kaitz index as we could get rid of crucial structural variations

[19]The Akaike Information Criterion (AIC) prefers larger number of lags. Because the fVAR model consists of 6-variable with time trend and exogenous quarterly dummy, the model becomes unstable if we use too many lags. This is why I choose p based on the SBC rather than the AIC.

in minimum wages. Instead, I control quarterly dummies $D_t = [D_{1t}, D_{2t}, D_{3t}]'$ where $D_{kt} = 1$ if it is kth quarter. I admit that it would be the n-th best way to deal with the issue, where $n \geq 1$, but I argue that it could be better to implement seasonal adjustment to the Kaitz index itself.

2.4 Identification assumption

In order to identify structural minimum wage shocks, I assume that 1) the Kaitz index (1) is the most *endogenous* variable among macroeconomic variables Y_t, 2) income distributions $\{\xi_{i,t}\}_{i=1}^{I}$ are more endogenous than aggregate variables Y_t and 3) $\xi_{i,t}$ is more exogenous than $\xi_{j,t}$ if $\xi_{i,t}$ explains more variations of the income density (3). 2) and 3) are normally assumed in the fVAR literature, driven by economic theory. Because macroeconomic variables are equilibrium & aggregation of cross-sectional distribution, it is a reasonable assumption.[20]

Given the above assumption, I identify the structural shock of Kaitz index, the intensity of minimum wages using the classical Cholesky decomposition (or called recursive identification). That is, I assume the order of exogeneity as $Z_t = \left[Y_t, \{\xi_{i,t}\}_{i=1}^{I}\right]$ where $Y_t = [\text{Emp}_t, \pi_t, \text{Kaitz}_t]$ – Employment rate is the most exogenous and $\xi_{3,t}$ is the most endogenous in this system.

The validity of assumption 1) is as follows. I assume that the Kaitz index is the most endogenous macroeconomic variable. If I used minimum wages, not the Kaitz index (1), then I could assume that minimum wage is the most exogenous variable in the system, as it is determined institutionally. However, the Kaitz index (1) is the intensity of minimum wages. Thus, it is not reasonable to assume that the Kaitz index is more exogenous than other macroeconomic variables, such as employment rate and inflation. As a robustness check, I show that the order of exogeneity of macroeconomic variables does not change the main result.

[20] To the best of our knowledge, there is no method to identify the exogeneity of functional factors. I acknowledge that the identification assumption here is not complete and it is necessary to develop a more rigorous econometric methods to identify structural shocks of cross-sectional distributions.

Discussion: Alternative identification strategy It is worth discussing the alternative identification strategy. The Minimum Wage Commission (MWC) in Korea announces the expected proportion of workers affected by minimum wage before the newly determined minimum wage policy is implemented. Thus, if we have quarterly micro data to measure the cross-sectional hourly wages, we can measure the forecasting error − the distance between announced proportion of workers affected by minimum wage and actual one ex-post, and the forecasting error could be a good alternative structural shock. If the HIES data included hours work information, it might be as good as identification strategy comparing with the recursive identification. Thus, I conservatively assume that the Kaitz index is the most endogenous macroeconomic variables.

3 Results

This section reports the results of fVAR analysis. Section 3.1 shows impulse response functions of macroeconomic variables and factors. Section 3.2 reports dynamic responses of income distribution with respect to minimum wage shocks. In Section 3.3, Section 3.3.1 and Section 3.3.2 show the roles of responses of low-income households and cross-sectional information through counterfactual exercises, respectively. Section 3.4 reports distributional responses of employment for household-heads for each income group.

3.1 Impulse response functions: Overall

Figure 4 shows the impulse response functions (IRFs) to one-unit shock to the Kaitz index.[21] As previously discussed, the Kaitz index is ordered as the most endogenous variable among the macroeconomic aggregates in the VAR system. Consequently, the other macroeconomic variables exhibit no contemporaneous responses (at period $t = 0$) to the minimum wage shock. In contrast, the income distribution factors (Dist. i) show immediate contempora-

[21] Main results are robust to considering a one-standard-deviation shock.

neous responses, reflecting the identifying assumption that cross-sectional distributions are more endogenous than the macroeconomic aggregates.

Following a one-unit minimum wage shock, Figure 4 indicates that the aggregate employment rate falls by approximately 1 percentage point, a decline that is statistically significant at the 68% confidence level upon impact. However, this effect dissipates and becomes statistically insignificant from the subsequent quarter onward. This suggests that the contractionary effect of a minimum wage increase is short-lived, largely because the minimum wage shock itself lacks persistence, as shown in panel (1,3). Regarding inflation, the response remains statistically insignificant over the entire 20-quarter horizon. Theoretically, a higher minimum wage can generate inflationary pressure by raising the labor earnings of employed workers and increasing firms' labor costs. On the other hand, it can also shrink aggregate demand if it reduces overall employment or income, and entrepreneurial business income. The insignificant net response implies that neither the cost-push nor the demand-contraction channel clearly dominates. In addition, if the positive minimum wage shock increases household's income at the bottom of distribution, given their higher marginal propensity to consume (MPC), we could expect higher inflation. The insignificant net effect indirectly implies that the positive effect of higher minimum wages on low-income households might be limited.

Finally, regarding the responses of the distributional factors (the second row of Figure 4), interpreting the dynamics of the factors themselves is not highly informative. Therefore, I investigate the functional impulse responses—the actual dynamic changes in the cross-sectional distributions backed out from these factors—in Section 3.2.

As a robustness check, I show in Appendix A that main results including functional responses discussed in Section 3.2 if the Kaitz index is the most exogenous variable.

3.2 Functional responses: Income distribution

Because the IRFs of the distributional factors lack direct economic interpretation, I compute the functional impulse responses to back out the dynamic distributional changes using the

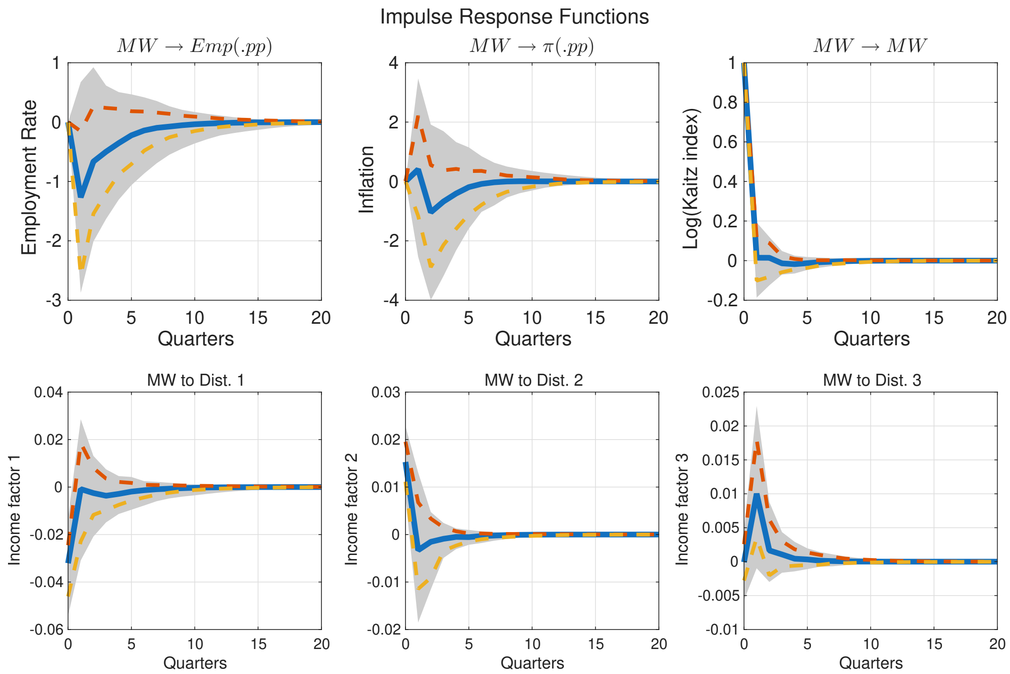


Figure 4: Impulse response functions – Benchmark model. Blue solid lines present median estimate, dotted lines present 68% confidence intervals and shaded areas present 90% confidence interval. MW means Minimum Wage, Emp means employment rate, π means inflation rate, Dist. i means factor i extracted from the FPCA. Confidence intervals are computed by bootstrap.

estimates from Figure 4. Figure 5 displays the percentage deviations of key cross-sectional moments—mean, standard deviation, Gini index, and coefficient of variation (CV)—from their steady states. First, mean income falls by approximately 1.5% in response to a one-unit minimum wage shock, a decline that is statistically significant. Regarding inequality measures, while the standard deviation of income does not respond significantly, the Gini index exhibits a statistically significant increase of approximately 1.5% upon impact before eventually returning to its steady state. Lastly, the CV increases significantly at the 68% confidence level upon impact—driven primarily by the decline in its denominator (mean income)—before the response becomes statistically insignificant. We can explain why the standard deviation of income decreases insignificantly but the Gini index increases significantly by examining the responses of income across deciles in Figure 6.

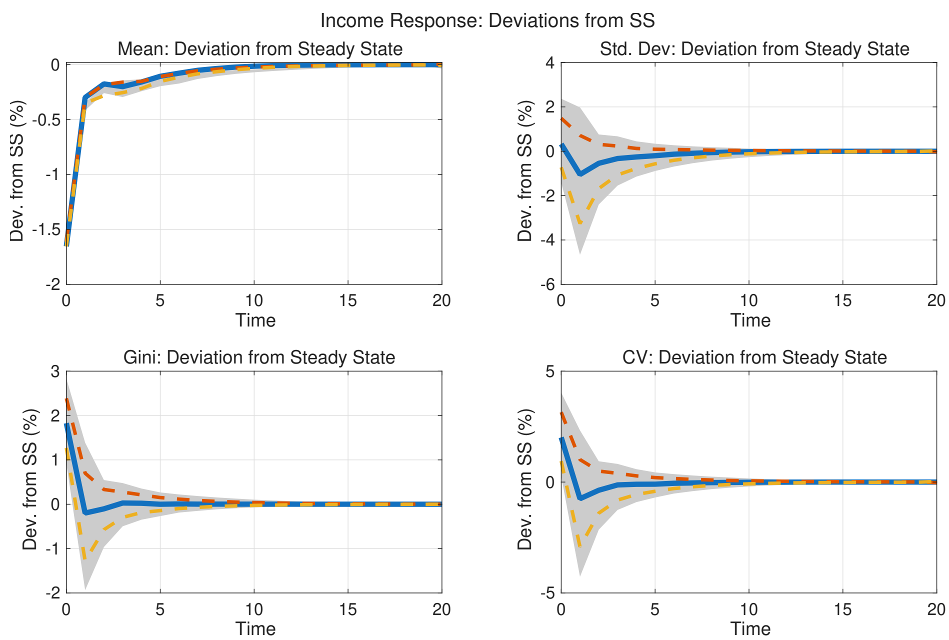


Figure 5: Functional impulse response functions: Mean, Standard deviation, Gini index, and Coefficient of variation (CV) − Benchmark model. Blue solid lines represent median estimates, dotted lines represent 68% confidence intervals, and shaded areas represent 90% confidence intervals. Confidence intervals are computed by bootstrap.

To provide a more granular view of these dynamics, Figure 6 reports the responses at specific income percentiles. Following a one-unit minimum wage shock, households across the entire distribution—from the 10th percentile (P10) to the 90th percentile (P90)—experience a decline in income. Furthermore, these negative effects are disproportionately more pronounced for households at the lower end of the distribution. For instance, panel (2,3) demonstrates that the income decline at the 30th percentile is more severe than at the 70th percentile, leading to a rise in the P70/P30 ratio. A similar widening of inequality is observed in the P90/P10 ratio.

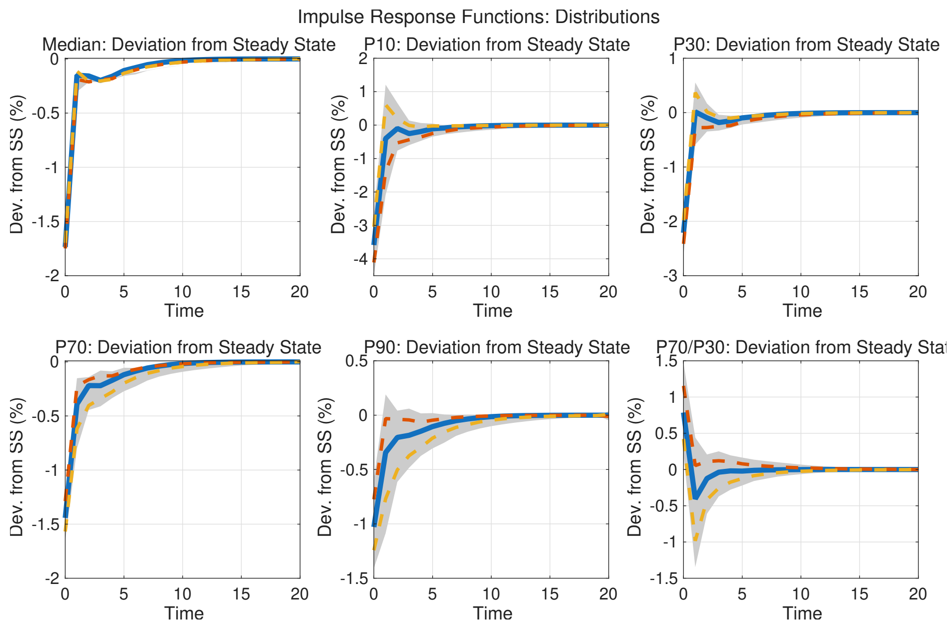


Figure 6: Functional impulse response functions: Median, P10, P30, P70, P90, and P70/P30 − Benchmark model. Blue solid lines represent median estimates, dotted lines represent 68% confidence intervals, and shaded areas represent 90% confidence intervals. Confidence intervals are computed by bootstrap.

The results imply that a higher minimum wage decreases income across all groups, but more importantly, it disproportionately affects lower-income households. As overall income shrinks, the first moment (mean) of the distribution decreases. Interestingly, while the standard deviation also exhibits a decline (albeit statistically insignificant) due to the reduction in absolute income differences, this does not imply an improvement in equity. Because the income contraction is much more severe at the bottom of the distribution, the relative share of total income held by low-income households diminishes. This worsening of relative inequality drives the significant increase in the Gini index.

Discussion: Mechanisms of Distributional Changes The income from HIES in Korea comprises labor, business, financial, and transfer income. For low-income households, the dynamics are primarily driven by labor and transfer income. As shown in Section 3.4, a higher minimum wage disproportionately reduces the employment rate of low-income households, which directly translates to a decline in their total labor earnings. Furthermore, as discussed by Kwon et al. (2025), transitioning into non-employment strips these households of eligibility for employment-contingent benefits, such as the Earned Income Tax Credit (EITC) and Child Tax Credit (CTC), thereby exacerbating their income loss.[22] In contrast, the transfer income of high-income households remains largely insulated from these shocks. While it is empirically challenging to isolate the exact magnitudes of these individual channels and their spillovers using micro-data alone, the fVAR estimates in this paper successfully capture their net general equilibrium effect on the aggregate economy.

3.3 Role of cross-sectional information

I further investigate how the dynamics of macroeconomic aggregates and the cross-sectional income distribution interact. To isolate these channels, Section 3.3 presents a counterfactual exercise in which the endogenous responses of low-income households are *partially* shut down, allowing for a comparison of the aggregate employment response against the benchmark model. Finally, in Section 3.3.2, I report the impulse response functions from a restricted model that entirely excludes the distributional factors.

3.3.1 The Role of Low-Income Households' Responses

As discussed in Section 2.3, I extract three factors using FPCA to efficiently approximate the cross-sectional income distribution. Because the distribution is approximated by finite factors, it is not mechanically possible to shut down the responses of a specific income

[22] Kwon et al. (2025) note that this reduction in tax credits may be partially offset by increases in pure public assistance programs for the unemployed, such as National Basic Livelihood Security (NBLS) benefits, Housing Benefits, and the Basic Pension.

group (i.e., shutting down only responses of the bottom 10%). However, I find that the first and second factors ($i = 1, 2$) largely govern the dynamics of low-income households. Therefore, I simulate a counterfactual scenario by zeroing out the impulse responses of these first two factors—corresponding to the (2,1) and (2,2) panels in Figure 4—across all horizons from $\tau = 0$ to 20.[23] Economically, this exercise might mimic a policy intervention where the government cushions low-income households against the minimum wage shock through targeted transfer expenditures, such as National Basic Livelihood Security (NBLS) benefits.

Figure 7 presents the functional impulse responses of each income percentile under this counterfactual scenario. Compared to the benchmark results in Figure 5, this intervention yields two main differences: 1) it mutes the contemporaneous responses and quantitatively dampens the overall functional responses, and 2) the disproportionately severe negative impacts on the 10th and 30th percentiles are significantly mitigated relative to higher-income groups.

To quantify the impact of these distributional dynamics on aggregate employment, I construct two cumulative response measures, drawing on the standard methodology for calculating cumulative fiscal multipliers. First, assuming an annual interest rate of 3.5%, I compute the present-value cumulative multiplier, defined as the discounted sum of employment rate changes divided by the discounted sum of minimum wage shocks over the 20-quarter horizon: $\frac{\sum_{\tau=0}^{20} \Delta \text{Emp}_{t+\tau}/(1+r)^\tau}{\sum_{\tau=0}^{20} \Delta \text{Kaitz}_{t+\tau}/(1+r)^\tau}$. Second, I compute a simple cumulative multiplier without discounting: $\frac{\sum_{\tau=0}^{20} \Delta \text{Emp}_{t+\tau}}{\sum_{\tau=0}^{20} \Delta \text{Kaitz}_{t+\tau}}$.

Table 1 reports these cumulative measures for both the benchmark and counterfactual models. The results indicate that when the endogenous income responses of low-income households are muted, the negative response of the aggregate employment rate is dampened by approximately 9.54% to 10.27%.

In conclusion, although this approach only partially shuts down the endogenous responses

[23] Although shutting down these responses over the entire horizon is restrictive, I implement the counterfactual exercise in this way because muting only the contemporaneous effects yields negligible quantitative differences.

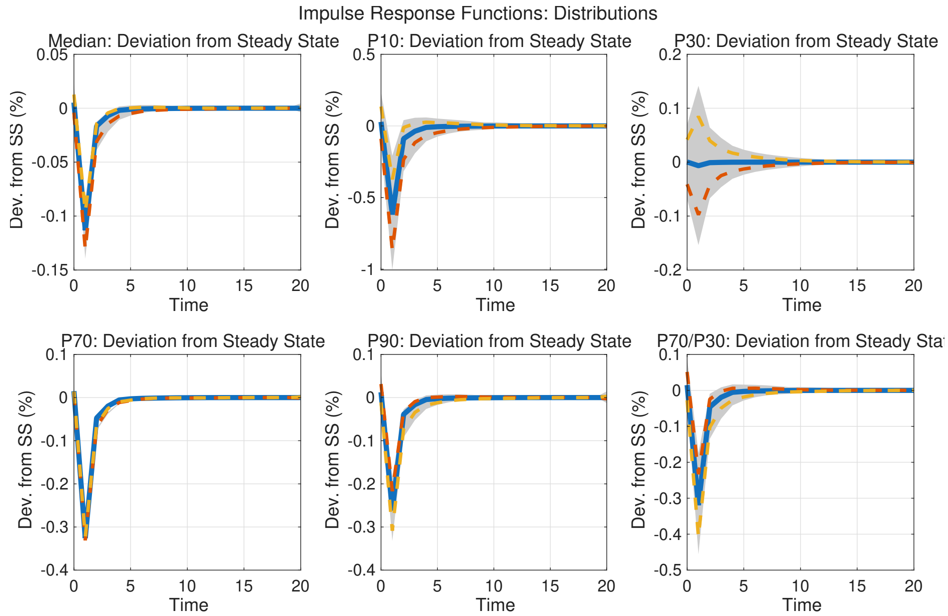


Figure 7: Functional impulse response functions (Counterfactual): Median, P10, P30, P70, P90, and P70/P30. Blue solid lines represent median estimates, dotted lines represent 68% confidence intervals, and shaded areas represent 90% confidence intervals. Confidence intervals are computed by bootstrap.

at the bottom of the income distribution, it provides empirical support for the notion that the macroeconomic employment effects of minimum wage shocks depend on the underlying cross-sectional distributional dynamics.

	Benchmark model	Counterfactual model	Percent change (%)
$\frac{\sum \Delta\text{Emp}_{t+\tau}/(1+r)^{\tau}}{\sum \Delta\text{Kaitz}_{t+\tau}/(1+r)^{\tau}}$	-3.5067	-3.1722	-9.54%
$\frac{\sum \Delta\text{Emp}_{t+\tau}}{\sum \Delta\text{Kaitz}_{t+\tau}}$	-3.6064	-3.2360	-10.27%

Table 1: Benchmark vs. Counterfactual: Cumulative aggregate employment rate responses. The benchmark model represents the results from Figure 5, while the counterfactual model reflects the exercise in Figure 7. The percent change is calculated as $100 \times (\text{Counterfactual}/\text{Benchmark} - 1)$.

3.3.2 Only macroeconomic aggregates: IRFs in the standard VAR model

Building on the counterfactual exercise in Section 3.3.1, I next estimate a standard VAR model restricted to only the macroeconomic aggregates. Specifically, I estimate (4) using $Y_t = [\text{Emp}_t, \pi_t, \text{Kaitz}_t]'$, explicitly excluding the cross-sectional income distribution.

[Figure 8](#) presents the impulse response functions from this restricted model. Compared to the benchmark results in Figure 4, the negative contemporaneous response of the aggregate employment rate to a minimum wage shock loses its statistical significance, even at the 68% confidence level. Furthermore, although it remains statistically insignificant, the median response of inflation shifts from negative to positive. Economically, this suggests that without accounting for the distributional drag on aggregate demand, the inflationary pressures arising from higher labor costs and the increased purchasing power of affected workers appear to outweigh the disinflationary pressures from economic slack.

Taken together with the findings in Section 3.3.1, these results demonstrate that incorporating cross-sectional distributional information is quantitatively crucial. Ignoring the feedback between the income distribution and macroeconomic aggregates could alter the macroeconomic implications of minimum wage shocks.

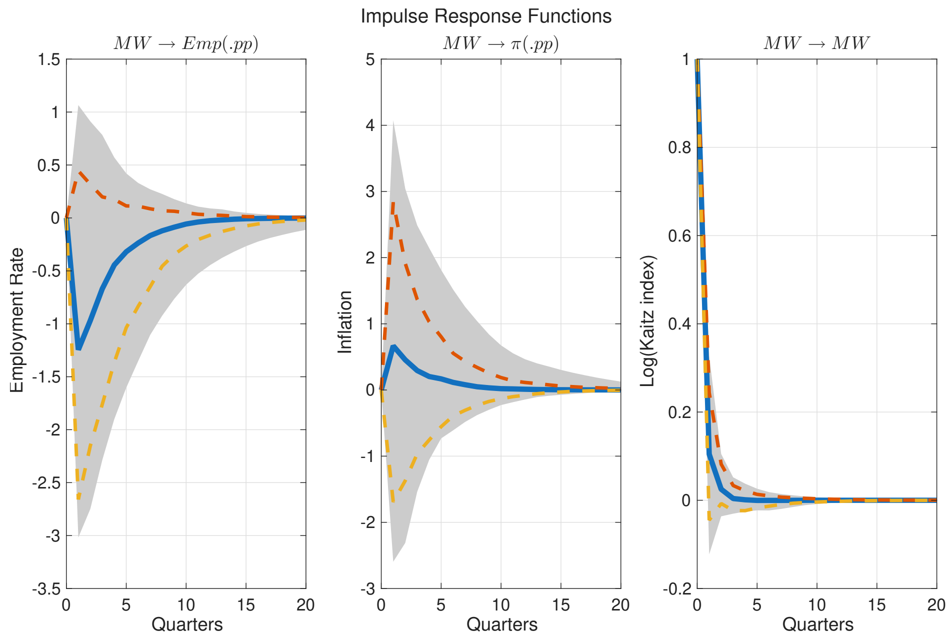


Figure 8: Impulse response functions — With only macroeconomic variables: Blue solid lines present median estimate, dotted lines present 68% confidence intervals and shaded areas present 90% confidence interval. MW means Minimum Wage, Emp means employment rate, and π means inflation rate. Confidence intervals are computed by bootstrap.

3.4 Functional responses: Employment rate over income

To further unpack these dynamics, I estimate the functional impulse responses of the household-head employment rate across the 200 income quantiles. Figure 9 presents these distributional employment responses. Consistent with the income dynamics documented in Section 3.2, the employment rate of household heads at the lower end of the income distribution suffers a substantially larger decline compared to their higher-income counterparts. This disproportionate drop in the extensive margin of employment has critical implications for total household resources. Because programs like the EITC and CTC are strictly tied to employment status, the heightened job loss among low-income workers directly disqualifies them from these in-work tax credits, thereby severely amplifying their overall income contraction. Consequently, these findings suggest that the minimum wage may be an inefficient policy tool for correcting wage markdowns in oligopsonistic labor markets, particularly for low-income households. This is consistent with Hurst et al. (Forthcoming)'s findings based on the calibrated structural model.[24]

4 Conclusion

This paper investigates the dynamic interplay between minimum wage shocks, income distribution, and macroeconomic aggregates in Korea using an fVAR model. The analysis yields three primary findings. First, a positive minimum wage shock disproportionately reduces the income and employment of low-income households, leading to a significant increase in the Gini index.

Second, this study demonstrates that incorporating cross-sectional information is quantitatively essential for explaining aggregate dynamics, addressing a key gap in the existing fVAR literature. While previous studies often found distributional factors to be secondary,

[24]To be specific, Hurst et al. (Forthcoming) demonstrate that minimum wage increases can become detrimental to low-income households if the policy increment is sufficiently large. Therefore, this argument holds provided that the magnitude of the structural minimum wage shocks identified in this paper is comparable to the policy changes simulated in their structural model.

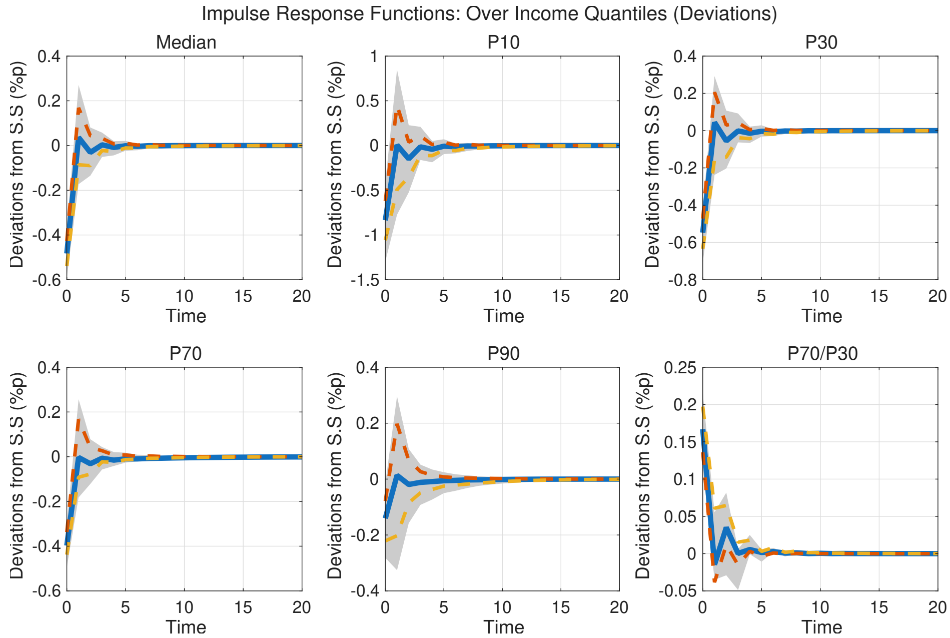


Figure 9: Impulse response functions of employment rate for household-head over income decile: Median, P10, P30, P70, P90 and P70/P30 − Benchmark model. Blue solid lines present median estimate, dotted lines present 68% confidence intervals and shaded areas present 90% confidence interval. Confidence intervals are computed by bootstrap.

I show that ignoring these feedbacks renders the negative aggregate employment effect statistically insignificant and masks the true inflationary pressures. Counterfactual exercises further reveal that the aggregate contraction is primarily driven by the endogenous responses of the bottom deciles. This highlights the importance of general equilibrium feedbacks—a central contribution of this paper—in capturing the full macroeconomic impact of labor market policies.

In conclusion, nationwide minimum wage hikes in Korea can inadvertently exacerbate inequality through disemployment effects, particularly when job losses disqualify vulnerable households from in-work benefits. These findings underscore the need for better coordination between minimum wage policy and social safety nets, while showcasing the fVAR framework's ability to capture complex micro-macro linkages that standard VARs overlook.

Declarations: Generative AI statement

During the preparation of this work the author used ChatGPT and Gemini in order to proofread the paper. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Appendices

A Most exogenous Kaitz index

Figure A.1, Figure A.2, and Figure A.3 present impulse response functions (IRFs), functional responses of income distribution for moments and each percentile if the Kaitz index is the most exogenous macroeconomic variable in the fVAR system.

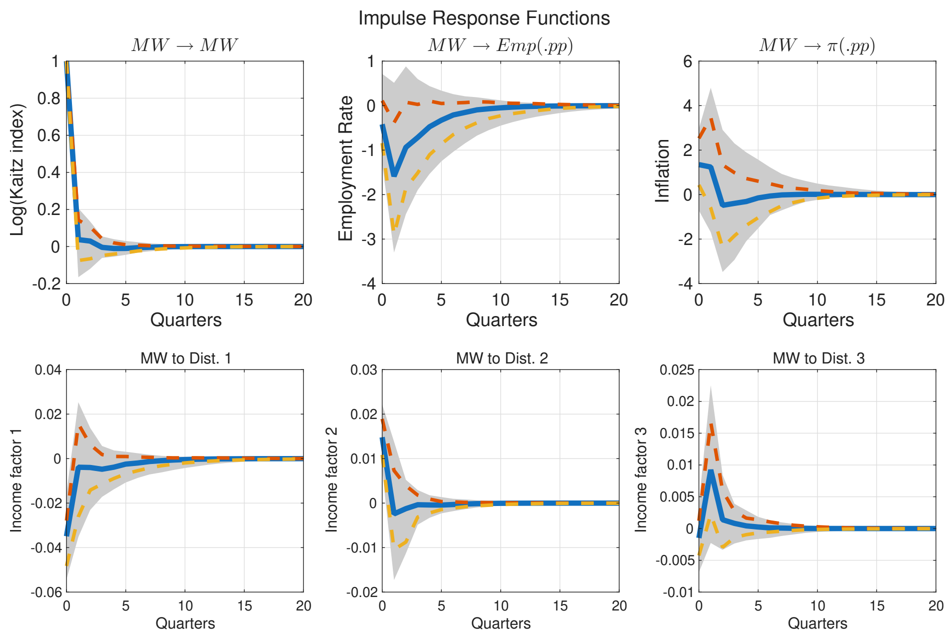

Figure A.1: Impulse response functions – Most exogenous Kaitz index. Blue solid lines present median estimates, dotted lines present 68% confidence intervals, and shaded areas present 90% confidence intervals. Confidence intervals are computed by bootstrap.

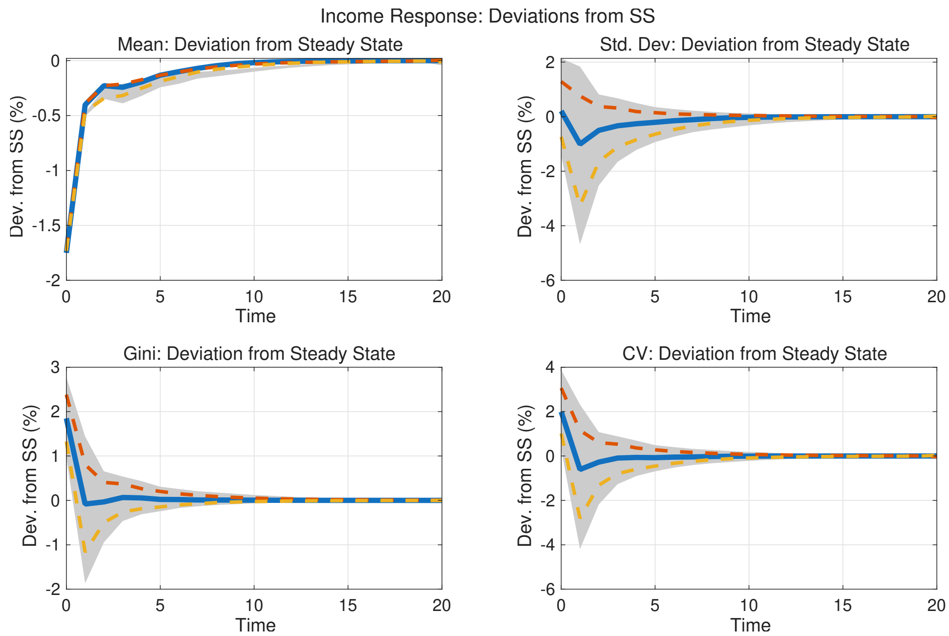

Figure A.2: Functional impulse response functions: Mean, Standard deviation, Gini index and Coefficient of variation – Most exogenous Kaitz index. Blue solid lines present median estimate, dotted lines present 68% confidence intervals and shaded areas present 90% confidence interval.

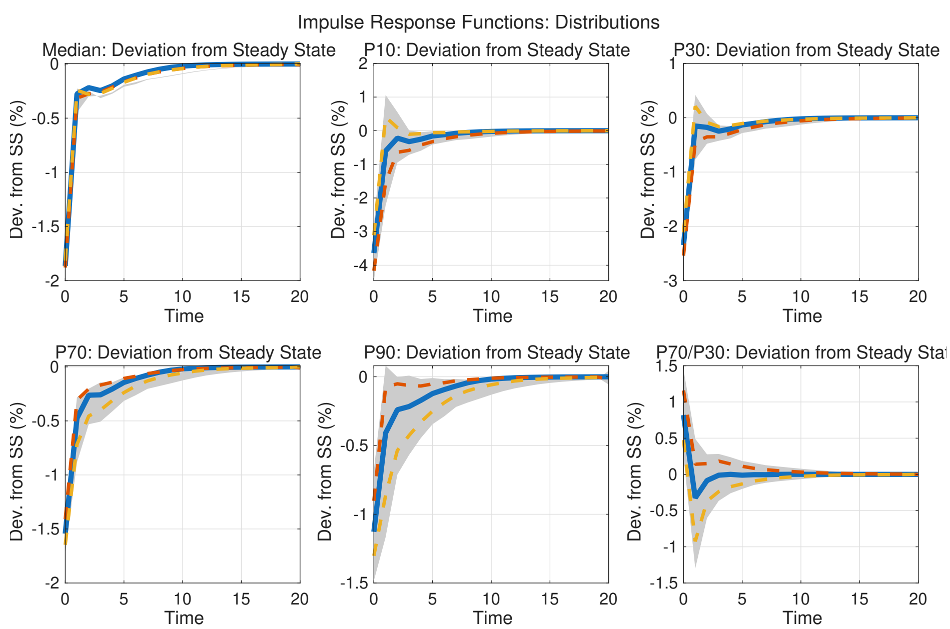

Figure A.3: Impulse response functions: Median, P10, P30, P70, P90 and P70/P30 – Most exogenous Kaitz index. Blue solid lines present median estimate, dotted lines present 68% confidence intervals and shaded areas present 90% confidence interval. Confidence intervals are computed by bootstrap.