Do Crisis Shape the Economic Structure?*

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Abstract

In this paper, we study whether crises accelerate or slow down structural change. We document the sectoral reallocation of economic activity following crises such as banking and sovereign debt crises, using data from 79 emerging and developed economies covering over 100 crisis episodes between 1950 and 2019. Our analysis reveals significant and persistent shifts in the aftermath of crises. On average, reallocation toward the agricultural sector delays structural transformation by 7 to 9 years, while reallocation out of the service sector is minimal. The construction sector experiences a severe collapse, whereas output shifts to manufacturing without a corresponding reallocation of employment. To understand these patterns, we use a model of growth and structural transformation with input and demand distortions. Our findings show that reallocation in agriculture and services is largely driven by standard income and price effects, while the excessive collapse in construction reflects a sharp relative increase in demand distortions. Additionally, the divergence between output and employment reallocation in manufacturing is explained by significant and persistent changes in labor distortions following a crisis.

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1 Introduction

As countries develop, they experience significant changes in their economic structure, shifting economic activity from primary sectors to manufacturing and eventually to services (Herrendorf, Rogerson and Valentinyi, 2014). However, the pace of this structural transformation varies widely across countries (Huneeus and Rogerson, 2020; Rodrik, 2016). One possible explanation for these differing paths is that some economies, particularly emerging ones, experience severe economic crises more frequently, which can have long-lasting effects not only on aggregate economic activity but also on its allocation across sectors.[1]

But do crises accelerate or slow down structural transformation? One classical view argues that crises "cleanse" the economy by improving resource allocation (Schumpeter, 1942; Caballero and Hammour, 1991), potentially accelerating structural transformation. In contrast, an alternative view suggests that crises have persistently negative effects on aggregate economic activity (King and Rebelo, 1988; Stadler, 1990), possibly delaying structural transformation. Systematic empirical evidence on the impact of crises on sectoral reallocation remains limited.

In this paper, we study empirically and quantitatively how crises shape the economic structure. First, we provide new empirical evidence on the extent and persistence of sectoral reallocation of economic activity following crises across a large number of countries and crisis episodes. Then, we quantify the drivers of reallocation during crises by extending workhorse models of structural transformation to include wedges (distortions), following an approach similar to that used in the business cycle accounting literature (Chari, Kehoe and McGrattan, 2007). Our findings show substantial and persistent reallocation during crises. While we observe a significant slowdown in structural transformation out of the agricultural sector, reallocation patterns among the remaining sectors are more ambiguous. Distortions play a key role in this process, particularly in driving labor out of manufacturing and economic activity away from construction.

For our empirical analysis, we use data from various sources on sectoral output (value

[1]Several papers, for example, Barro (2006); Cerra and Saxena (2008), have documented large and persistent aggregate output contractions following crises, and Aguiar and Gopinath (2007) highlights that these shocks are more common in emerging economies.

added) and employment across countries and combine it with crisis dating information. Our baseline sample consists of 79 countries and over 100 episodes of major financial crises, including both banking and sovereign debt crises, spanning the period from 1950 to 2019.

Our crisis-event analysis shows significant and persistent sectoral reallocation in employment and output in the aftermath of crises. First, the agricultural sector experiences a sustained 6% increase in output and employment shares, persisting for at least a decade, while the construction sector undergoes a nearly 15% persistent decline in both shares. In manufacturing, we observe a substantial and lasting rise in output shares, but a modest 1% increase in its employment share. Finally, while reallocation between the service sector and other sectors is minimal, there is substantial reallocation within the service sector itself.

Next, we explore the dynamics of relative prices and find a significant increase in the manufacturing sector's prices relative to other sectors, suggesting that price effects may play a key role in driving reallocation between manufacturing and other sectors during crises. Finally, we analyze the results across emerging and developed economies. In developed economies, we observe greater reallocation toward agriculture and minimal reallocation between manufacturing (excluding construction) and services. Meanwhile, the patterns in emerging economies closely align with our baseline findings.

Overall, the results suggest that crises significantly delay structural change from the agriculture sector to other sectors. However, the patterns observed in the construction, manufacturing, and services sectors indicate a more nuanced story. There is significant and persistent reallocation out of the construction sector, output shifts to the manufacturing sector without a corresponding increase in employment, and reallocation out of services is limited and heterogeneous. These patterns do not align clearly with either a strong delay or acceleration in structural transformation toward services following a crisis.

To study the factors driving sectoral reallocation after a crisis, we extend an off-the-shelf model of structural transformation, based on Comin, Lashkari and Mestieri (2021), to include sector-specific wedges (distortions) in production inputs and demand, similar to the approaches of Chari *et al.* (2007) and Hsieh and Klenow (2009).

By fitting the post-crisis dynamics, we explore the roles of standard income and price effects, as well as distortions during crises.

A reduction in aggregate consumption during crises reallocates resources from high-income elasticity sectors, such as services, to low-income elasticity sectors, such as agriculture. Moreover, changes in relative prices across sectors—driven by changes in productivity and distortions across sectors—would reallocate resources toward sectors experiencing larger price increases if the elasticity of substitution between goods is less than one; otherwise, the opposite occurs.

In addition, in our model, the differences between labor and value-added dynamics across sectors provide insights into changes in labor wedges across sectors—distortions to marginal labor costs. Given the relative prices, a relatively larger labor wedge in one sector will lead to a reallocation of labor out of that sector, but no corresponding reallocation of value-added. In addition, demand wedges—which reflect changes in consumption wedges and demand shifters—account for the value-added dynamics not explained by relative prices and aggregate consumption. For instance, a credit crunch that reduces consumption in the sector would manifest in higher demand distortions.

Using manufacturing as the base sector, we show that standard income and price effects explain well the relative output dynamics in the agriculture and service sectors but fail to account for the pronounced relative decline observed in the construction sector during crises. Thus, demand wedges play a critical role in explaining the additional contraction in the construction sector. Finally, the income and price channels are not able explain the labor reallocation between manufacturing and other sectors. As a result, we find persistent changes in the labor wedge following crises that shift employment from the manufacturing to other sectors.

Contribution and Related Literature. The main contribution of this project is to deepen our understanding of the implications of large crises and how these can inform theories of long-run growth and structural transformation.

First, we contribute to the extensive literature on the substantial and persistent contraction in aggregate economic activity following crises (see, for example, Calvo (1998); Kehoe and Prescott (2007); Barro and Ursua (2008); Reinhart and Rogoff (2009), among others) by systematically examining the heterogeneous post-crisis dynamics across sectors for various countries and episodes, for which systematic evidence remains relatively scarce.[2] Our sample includes almost 80 countries across the entire development spectrum and around 100 crisis episodes since 1950.

Furthermore, previous work on crises and sectoral reallocation has mostly focused on analyzing the relationship between economic crises and reallocation between tradable and non-tradable sectors (see, for example, Schneider and Tornell (2004); Kehoe and Ruhl (2009); Pratap and Urrutia (2012); Kalantzis (2015); de Ferra (2016); Arellano, Bai and Mihalache (2018), among others). While we find reallocation from non-tradable to tradable sectors, consistent with previous work, we also document significant reallocation within non-tradable sectors, such as between construction and services, as well as within the services sector itself. Additionally, we observe notable differences in the dynamics of employment and output in manufacturing. Importantly, these reallocation patterns persist well beyond the crisis. Lastly, we complement previous work by quantifying the role of income and price effects and documenting the post-crisis dynamics of wedges that can be used to inform theories of crises and sectoral reallocation.

We also contribute to the extensive structural transformation literature (see, the review by Herrendorf *et al.* (2014)) by arguing that post-crisis dynamics can be informative of theories of structural change across sectors. Our findings suggest that persistent changes in distortions, especially in manufacturing and construction sectors, can play an important role in the heterogeneous paths of structural transformation. Drawing on the business cycle accounting literature (Chari *et al.*, 2007), we conduct a crisis accounting exercise using a standard model of structural transformation (Comin *et al.*, 2021) that incorporates production input and demand distortions.[3] This approach allows us to study the channels through which crises shape the economic structure in both the short and long run.[4]

Lastly, our paper contributes to a limited body of research linking economic downturns to structural change. Howes (2022) argues that structural transformation out

[2] Notable recent exceptions are Donovan, Lu, Pedtke and Schoellman (2024) and Müller and Verner (2023), which focus on the systematic impact of crises on labor markets and credit across sectors, respectively.

[3] Sposi, Yi and Zhang (2018) and Marcolino (2022) augment models of structural change with wedges to study long-run structural change patterns in Hungary, Portugal, and South Korea and in the US, respectively.

[4] In related work, Oberfield (2013) find that distortions between sectors play a significant role in explaining the post-crisis dynamics of the 1982 Chilean crisis.

of manufacturing in the U.S. accelerates following recessions. In contrast, our findings—based on a significantly larger set of countries and a broader range of sectors—show that post-crisis reallocation out of manufacturing in developed economies is limited and that crises may slow structural transformation, for example, by reallocating economic activity toward agriculture. Rubini and Moro (2024) examines the cyclical properties of models of structural transformation and finds they align with the data. Consistent with their findings, we observe that during crises, income and price effects effectively explain the dynamics of sectoral economic activity, except in the construction sector and the differing trajectories of employment and output in manufacturing. In our model, these discrepancies are captured residually by wedges in production inputs and demand.

This paper is organized as follows: Section 2 provides a description of the data; Section 3 presents the empirical patterns of sectoral reallocation following a crisis; Section 4 describes a model of structural transformation with distortions; and Section 5 combines the model with data to study the drivers of post-crisis sectoral reallocation.

2 Data

To empirically study the dynamics of sectoral reallocation during and after large crises, we combine newly developed historical data on sectoral employment and value-added with data on crisis dates. This section provides a detailed description of the datasets and the sample selection criteria used in our analysis.

2.1 Data Sources and Sample Selection

Sectoral Employment and Value Added. We use sectoral data on employment and value added from several data sources: the Groningen Growth and Development Centre (GGDC) 10-Sector Database, the GGDC/UNU-WIDER Economic Transformation Database, EU KLEMS (2023 and 2009 releases), and OECD STructural ANalysis Database. These datasets are widely used in the literature that studies structural transformation and growth (Gollin and Kaboski, 2023). Our dataset includes ten disaggregated sectors: agriculture, manufacturing, construction, utilities, mining, wholesale and retail trade, transportation, finance and real estate activities, health and education (government), and other services. In our baseline analysis, we focus on four main sectors: agriculture, construction, manufacturing, and services excluding utilities and government services.[5] Moreover, we use nominal and real value added data to compute the country-level sectoral price indexes.

Crisis Dates. We use the dates for banking crises and sovereign debt defaults from 1970 to 2017 provided by Laeven and Valencia (2018), extending the coverage to the pre-1970 period with sovereign default and banking crisis dates from the Global Crises Data by Country dataset, as well as additional banking crisis dates from Baron, Verner and Xiong (2020).[6] We define a crisis episode as occurring when there is either a sovereign debt crisis or a banking crisis, and we restrict our analysis to crisis dates not preceded by a crisis in the previous four years. Our baseline sample comprises 102 crisis episodes, encompassing 79 banking crises and 36 sovereign debt default crises (Table 1). Within these episodes, 13 instances involve both a banking crisis and a sovereign debt default crisis simultaneously. The majority of these episodes are observed in emerging economies. In addition, 61 of the baseline crisis episodes involved a significant output growth reversal, while 39 were characterized by a large currency devaluation.[7]

National Accounts and Real Exchange Rate. To measure the income level and its dynamics we use GDP, consumption, and population data from Penn World Tables (PWT) and World Bank-World Development Indicators (WDI). Following Schmitt-Grohé and Uribe (2018) and Kohn, Leibovici and Tretvoll (2021), we define *Developed* economies as those with a GDP per capita exceeding $25,000 USD, and *Emerging* as those not meeting this threshold.[8] Finally, we use real exchange data from WDI-World Bank, Bank of

[5]We exclude mining, since its share is close to zero in several countries and crisis episodes.

[6]Laeven and Valencia (2018) dataset is an update of Laeven and Valencia (2013). The Global Crises by Country dataset (https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/global.aspx) is developed by The Behavioral & Financial Stability Project based on data collected by Carmen Reinhart, Ken Rogoff, Christoph Trebesch, and Vincent Reinhart over several years.

[7]We consider a large output reversal episode as a crisis where the aggregate output annual growth rate is at least 1% lower two years after the crisis than it was the eight years before the crisis. Additionally, a large devaluation episode is defined as one in which there is a currency crisis occurring between the year before and two years after the crisis, as defined by Laeven and Valencia (2018).

[8]Due to data availability, for the country classification we use the average GDP per capita PPP in 2017 USD from WDI for the period after 1990.

Table 1: Frequency and Type of Crisis Episodes

	All	Emerging	Developed
All	102	78	24
Banking	79	55	24
Sovereign debt default	36	35	1
Large growth reversal	61	40	21
Large devaluation	39	36	3

Notes: Table shows the number of crisis episodes in our baseline sample. We include the crisis episodes for which sectoral employment or value added data is available for all the sectors considered in the analysis.

International Settlements (BIS), and Bruegel.

Sample Selection. In our sample, we select countries with a population greater than 1.5 million and remove the country-year observations for which we don't have observations in all our main sectors (agriculture, manufacturing, construction, and services). The baseline sample includes 79 countries—52 emerging and 27 developed economies— spanning the period 1950-2019. Table A.1 and Table A.2 show the list of the countries included in our baseline sample. Figure A.2 shows the distribution of output per capita for the entire sample. When crises occur, we observe that the included episodes span a wide range of the development spectrum. The countries in our sample represent 80% to 90% of the global GDP.

2.2 Cross-Section Structural Patterns

To characterize the economic structure of an economy, we use the employment and value-added shares across sectors. These shares are calculated as the employment or value-added of each sector divided by the total employment or value-added across all sectors. Next, we present summary statistics on the distribution of output and employment across sectors and describe the structural transformation patterns observed in our baseline sample.

Sectoral Shares Distribution. Table 2 displays the distribution of employment and value-added shares across sectors for the entire sample and conditional on the crisis window, defined as the period from 2 years before to 2 years after the crisis. In our sample, the average economy exhibits agriculture employment and value-added shares of 36% and 16%, respectively. On the other hand, service employment and value-added shares are 40% and 51%, respectively. The manufacturing sector represents 17% of employment and 22% of value added, while the construction sector holds a smaller share, accounting for approximately 7% of both employment and value added. The shares of employment and value added across sectors are similar in both the entire sample and the crisis window. Additionally, there is considerable dispersion in the employment and value-added shares, particularly within the agriculture and service sectors.[9]

Table 2: Sectoral Shares Distribution (%)

	Employment				Value Added			
	Mean	P25	P50	P75	Mean	P25	P50	P75
a. All sample								
Agriculture	36	9	28	60	16	4	11	25
Manufacturing	17	10	16	23	22	16	22	27
Construction	7	3	7	9	7	5	7	8
Services	40	23	41	57	51	42	51	60
b. Crisis window								
Agriculture	35	11	28	60	15	5	11	21
Manufacturing	17	12	16	22	23	17	22	27
Construction	7	4	7	9	6	4	6	8
Services	41	23	41	58	51	42	49	60

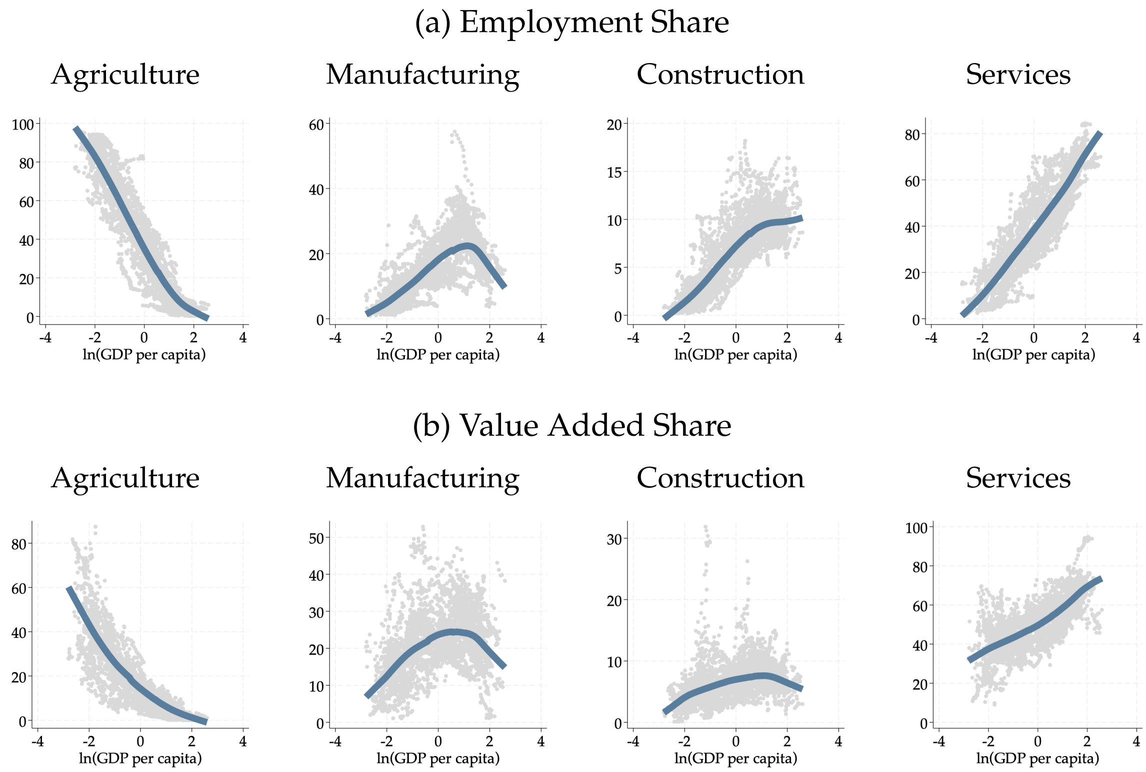
Notes: Table shows the value added and employment shares in percentage for each sector. Panel (a) shows for all the sample and Panel (b) the values around crisis. Services includes wholesale and retail trade, transportation, finance and real estate activities, and other services.
Data source: Penn World Tables, and Groningen Growth and Development Center.

Structural Transformation. It is well documented that the shares of employment and value added for different sectors varies significantly across the development spectrum (see, for example, Herrendorf *et al.* (2014)). In Figure 1, we illustrate the structural transformation patterns observed in our dataset. Consistent with findings from other studies, the share of the agricultural sector decreases significantly with GDP per capita levels, while the share of services increases. Moreover, the share of manufacturing exhibits an inverted U-shaped relationship with income. Additionally, we observe that the construction sector follows a pattern similar to that of the manufacturing sector.

[9] Table A.3 shows the employment and value-added shares for other sector categories.

Figure A.1 shows the structural transformation patterns for more dissagregated goods and services sectors.

Figure 1: Structural Transformation Patterns



Notes: The figure shows the share of value added and employment across the level of income, measure in terms of log GDP per capita PPP. The log GDP is normalized by 0 relative to the sample's median. Each point is a country-year observation and the solid lines are the locally weighted smoothing of observed shares. Services includes wholesale and retail trade, transportation, finance and real estate activities, and other services.
Data source: Penn World Tables, and sectoral data sources described in Section 2.1.

3 Post-Crisis Sectoral Reallocation

In this section, we conduct an event analysis to study the reallocation dynamics after crises. First, we study the aggregate dynamics of GDP, consumption, and the real exchange rate in the crisis. Next, we study how economic activity gets reallocated following a crisis.

3.1 Aggregate Dynamics

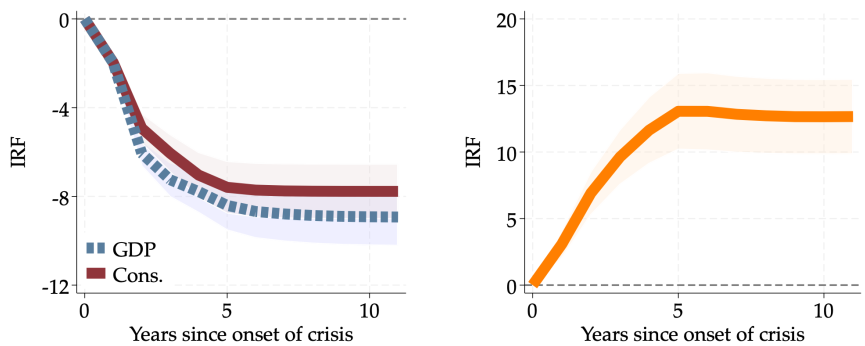
For our baseline event analysis we estimate the following empirical model:

$$\Delta \ln y_{it} = \alpha_i + \sum_{j=1}^{J} \beta_j \Delta \ln y_{it-j} + \sum_{h=0}^{H} \gamma_h D_{it-h} + \varepsilon_{it} \tag{1}$$

where $\Delta \ln y_{it}$ is the annual change of the variable studied for country i in year t (for example, GDP), α_i is a country fixed effect, and D_{it} is a dummy variable indicating if the first year of the crisis is at period t. Using the estimated values of $\{\beta, \gamma\}$, we construct the impulse response function of variable y_{it} to the crisis.[10]

Figure 2: Macro Dynamics During Crises

(a) Output and Consumption (b) Real Exchange Rate



Notes: The Figure shows the IRF of aggregate real output per capita (GDP), consumption per capita (Cons.), and the real exchange (REER) for the baseline crisis episodes using empirical model (1). The impulse response shows the estimated percentage point impact on real GDP from a crisis using the estimated coefficients. The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. Further details regarding the sectoral data and crisis episodes definitions are in Section 2.
Data sources: described in Section 2.1.

We study the dynamics of output, consumption, and the real exchange rate during the crisis. Figure 2 Panel (a) shows that output drops persistently by around 8% ten years after the crisis, as documented by Cerra and Saxena (2008). Additionally, aggregate consumption mirrors the persistent decline in output. The large and persistent consumption adjustments during the crisis are consistent with those documented by

[10] This empirical specification is based on Cerra and Saxena (2008) and is also employed by Guntin, Ottonello and Perez (2023) for sudden stop episodes and by Blanco, Ottonello and Ranosova (2022) to study inflation surges. The cumulative response, $\ln \hat{y}_{t+h} - \ln \hat{y}_t$, of the variable y_t from time t to $t+k$, where k denotes the number of periods since the onset of the crisis, is given by: $\ln \hat{y}_{i+h} - \ln \hat{y}_t = \sum_{k=1}^{h} \left\{ \mathbf{1}_{\{k \leq 5\}} \gamma_{k-1} + \mathbf{1}_{\{k>1\}} \sum_{j=1}^{\min\{k-1,4\}} \beta_j \Delta \ln \hat{y}_{t+k-j} \right\}$. This response can be constructed recursively using the estimated coefficients $\{\gamma, \beta\}$.

Barro and Ursua (2008) and others. Moreover, Panel (b) shows that the real exchange rate increases persistently after the crisis, by almost 15%, even ten years later, consistent with patterns documented by Calvo, Izquierdo and Talvi (2006) for several Sudden Stop episodes.[11]

Furthermore, Figure A.3 shows the aggregate dynamics for other types of crises: large growth reversals, large devaluations, banking crises, and sovereign debt crises. Similar to our baseline episodes, these events exhibit a persistent decline in output of approximately 8% to 15%, while the real exchange rate increases by 10% to 30% ten years after the crisis. As expected, the largest increases in the real exchange rate are observed during large devaluation and sovereign debt default episodes (Na, Schmitt-Grohé, Uribe and Yue, 2018).

3.2 Sectoral Dynamics

Next, we study output and employment reallocation across sectors. We use a similar empirical model to estimate the sectoral dynamics:

$$\Delta \ln s_{it}^k = \alpha_i^k + \sum_{j=1}^{J} \beta_j^k \Delta \ln s_{it-j}^k + \sum_{h=0}^{H} \gamma_j^k D_{it-h} + \varepsilon_{it}^k \tag{2}$$

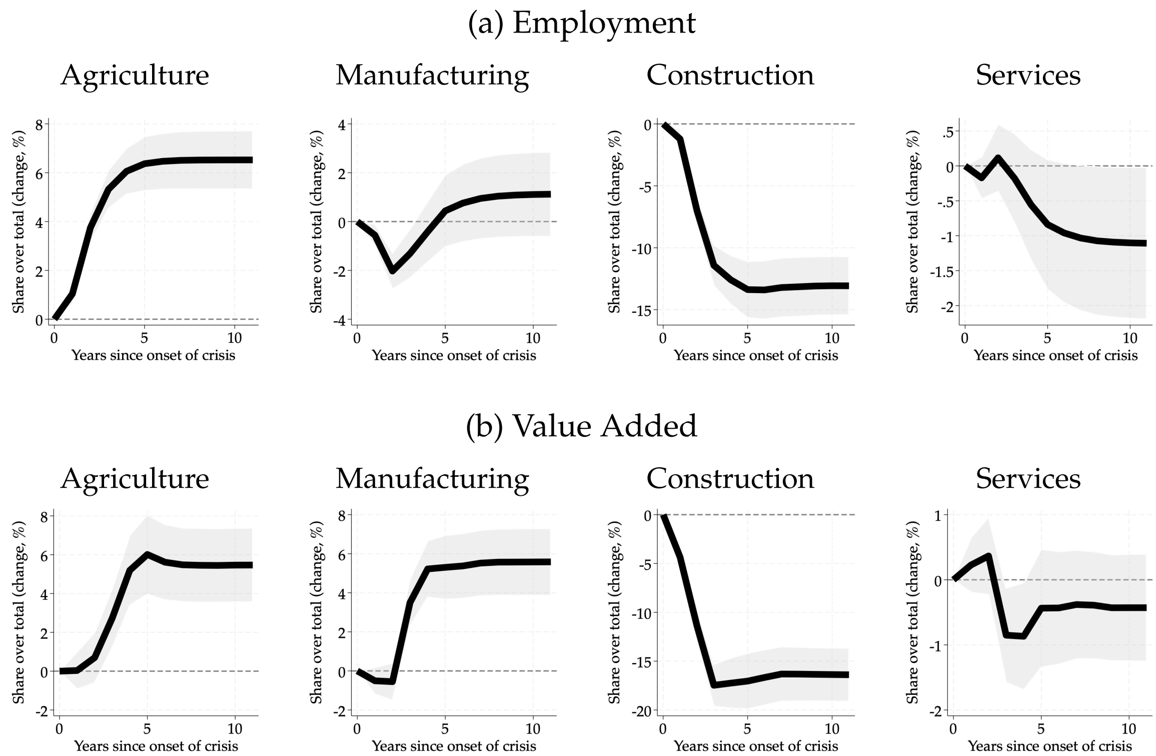
where s_{it}^k is the employment or value added share of sector k. We winsorize the growth rates at the top and bottom 0.5% and use a balanced panel. We show the results for our baseline exercise, different types of crises, across the development spectrum, dynamics within service sectors, sectoral prices impact, and robustness of our baseline results using local projections.[12]

Figure 3 shows the estimated cumulative changes in log shares for the agriculture, manufacturing, construction, and services sectors. Notably, we observe significant and persistent reallocation toward the agricultural sector following a crisis. The employment share of the agricultural sector increases persistently by nearly 7%, while the value-added share rises by approximately 6%. To illustrate the magnitude, a back-of-the-envelope calculation suggests that the reallocation toward the agricultural sector

[11] Our baseline sample includes various Sudden Stop episodes.

[12] We don't find significant differences if we include year fixed effects.

Figure 3: Sectoral Reallocation during Crisis



Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using the model (2). The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

during one crisis is equivalent to a delay of 7 to 9 years in structural transformation, relative to an economy growing at 1% annually.[13]

In contrast, the manufacturing sector initially experiences a decline in its employment share of about 2%, which subsequently recovers, leaving it nearly unchanged after 10 years. Notably, the value-added share of the manufacturing sector behaves differently, increasing by around 6% even ten years after the crisis. These patterns contrast sharply with those observed in the construction sector, where employment and value-added shares decline by 12% and 16%, respectively, indicating substantial reallocation away from this sector following the crisis. As we saw in 2.2, both, the manufacturing and construction sector have a non-monotone relationship with development. Thus, the extent to which this form of reallocation accelerates or slows the pace of structural

[13]This calculation uses the elasticity of aggregate output with respect to the agriculture value-added/employment shares ξ_{AGR} : $\ln s_{it}^{\text{AGR}} = \alpha + \xi_{\text{AGR}} \ln \text{GDP per capita}_{it} + \varepsilon_{it}$ and the values of the IRF in Figure 3 $\Delta^{10}\hat{s}^{\text{AGR}}$ such that the years to undo the reallocation is years$\,(\text{AGR}) = \frac{\Delta^{10}\hat{s}^{\text{AGR}}}{\Delta y \xi_{\text{AGR}}}$ where Δy is the assumed annual growth.

transformation depends on the level of development at the time of the crisis.

Finally, we observe that employment and value-added in the service sector shares decrease, though not significantly, with a decline of only about 1%. Therefore, we observe only a slight delay in structural transformation toward services.

Furthermore, we examine how these patterns vary across different types of crises, between emerging and developed economies, within more disaggregated service sectors, and using alternative empirical models, such as local projections. Additionally, we analyze the dynamics of sectoral prices during crises, which may play a crucial role in explaining reallocation across sectors.

Emerging vs Developed. In Figure A.5, we compare the dynamics of crisis episodes in Emerging and Developed economies. Overall, the employment share post-crisis dynamics appear similar across both types of economies. However, quantitatively, we observe a greater reallocation toward agriculture and out of construction in developed economies. On the other hand, the dynamics of value-added shares differ. In developed economies, we observe that manufacturing value-added share remains unchanged, with a slight increase in services share. Thus, during crises, output reallocation occurs primarily from construction toward agriculture and services. In contrast, in emerging economies, the share of the manufacturing sector increases while that of services slightly decreases.[14] Therefore, in emerging economies, crises lead to reallocation from the service and construction sectors toward agriculture and manufacturing, consistent with previous findings that reallocation during crises occurs from non-tradable to tradable sectors (see, for example, Kehoe and Ruhl (2009) for Sudden Stops in emerging economies). In addition, we observe that, unlike value added, employment is not being reallocated to the manufacturing sector, as in our baseline results.

Types of Crisis. We examine whether the patterns differ for other types of crises. Figures A.7 and A.8 show the dynamics during crises characterized by large currency devaluations and significant growth reversals, respectively. Regarding large devaluations, we find that the patterns are both qualitatively and quantitatively similar to those

[14] The same patterns emerge when studying how reallocation changes across income and consumption per capita levels using a continuous variable instead of classifying by income/consumption groups.

observed in baseline crisis episodes. Furthermore, we note a greater reallocation of resources when the crisis entails a substantial aggregate growth reversal. On the other hand, Figures A.9 and A.10 reveal some heterogeneity between banking and sovereign debt crises. In banking crises, we observe slightly less reallocation, but the patterns are overall consistent with our baseline results. In sovereign debt crises, consistent with Arellano *et al.* (2018), we observe a greater degree of reallocation from non-tradable to tradable sectors. Interestingly, unlike other sets of crisis episodes and our baseline results, we find that during sovereign debt crises, employment is reallocated toward manufacturing.

Service Sectors. Figure A.11 shows the dynamics within more disaggregated service sectors, including Wholesale and Retail Trade, Transportation, Finance and Real Estate, and Other Services (e.g., personal and entertainment). We observe heterogeneity across these sub sectors: Employment is reallocated most significantly out of Finance and Real Estate, to a lesser extent from Other Services and Transportation, while more employment is allocated to Wholesale and Retail Trade. In addition, the share of value added decreases for Finance and Real Estate, remains roughly unchanged for Other Services, and increases for Wholesale and Retail Trade and Transportation. This heterogeneity within service sectors shows that although we observe mild reallocation across aggregate services, there is substantial reallocation occurring within the service sector itself.

Local Projections. Alternatively, we estimate the crisis dynamics of employment and value-added shares using local projections (Jordà, 2005). We estimate

$$\ln s^k_{it+h} - \ln s^k_{it} = \alpha^{kh}_i + \beta^{kh} D_{it+1} + \gamma^{kh} \mathbf{Z}_{it} + \varepsilon^{kh}_{it+h}$$

where s^k_{it} is the employment/value-added share in period t for country i and sector k, D_{it+1} indicates if the first period of the crisis is at $t+1$, α^{kh}_i denotes the country fixed effects, and $\mathbf{Z}it$ is a vector of control variables. We include the level of income, the sectoral share level at t, and pre-crisis share growth as control variables to ensure that our findings are not driven by pre-crisis trends. The coefficient β^{kh} captures the dynamics h periods after the crisis began for sector k. We estimate it over the window

$h \in [-10, 10]$. Figure A.13 shows the results. We find the same results both qualitatively and quantitatively.

Sectoral Prices. Figure A.12 shows the dynamics of sectoral prices, normalized by those of the manufacturing sector. We observe a significant and persistent drop in the relative prices of agriculture, construction, and services during the crisis, by approximately 6%, 9%, and 4%, respectively, relative to manufacturing sector prices. This suggests that part of the reallocation to the manufacturing sector is driven by relative price changes. In the next sections, we will use the model to quantify how post-crisis dynamics of relative prices contribute to the observed reallocation.

4 Model of Structural Transformation with Distortions

In this section, we study what drives sectoral reallocation after crises. For this purpose, we use the model developed by Comin *et al.* (2021), which incorporates both demand and supply forces driving structural change. This model encompasses standard mechanisms widely studied in the literature: relative prices and heterogeneous productivity growth (Ngai and Pissarides, 2007), heterogeneous capital intensities (Acemoglu and Guerrieri, 2008), and non-homothetic preferences (Buera and Kaboski, 2009; Herrendorf *et al.*, 2014). We extend the model by introducing time-varying wedges into firms' input choices and households' consumption decisions, following the approach of the business cycle accounting literature (Chari *et al.*, 2007). By fitting the model to the data, we can quantify the channels driving the reallocation observed following a crisis documented in our empirical section.

4.1 Setup

4.1.1 Environment

The model is a discrete time general equilibrium model with multiple sectors. Households have nonhomothetic CES preferences over a discrete set of goods and services $\mathcal{I}$. Firms produces with a constant return technology and have heterogeneous sectoral productivity growth and capital intensities.

Households. Assume preferences over consumption c_t are

$$\sum_{t \geq 0} \beta^t \frac{c_t^{1-\theta} - 1}{1-\theta}$$

where $\beta \in (0,1)$ is the subjective discount factor and θ determines the intertemporal elasticity of substitution. Households aggregate consumption implicitly by

$$c_t = \left[\sum_{i \in \mathcal{I}} \gamma_{it}^{\frac{1}{\sigma}} \left(\frac{c_{it}}{c_t^{\varepsilon_i - 1}} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where c_{it} is the consumption of good i, ε_i is the income elasticity for good i, σ determines the subsitution across goods, and γ_{it} is the time-varying demand shifter that captures changes in demand unexplained by prices and income (e.g., consumption adjustment due to a credit crunch). In addition, households can save in risk-free asset a_t with return r_t, provide one unit of labor inellastically at wage w_t, and buy goods at prices $\{p_{it}\}_{i \in \mathcal{I}}$. Their budget constraint is

$$\sum_{i \in \mathcal{I}} p_{it} \left(1 + \tau_{it}^c\right) c_{it} + a_{t+1} \leq w_t + a_t \left(1 + r_t\right),$$

where τ_{it}^c is a time-varying wedge that captures differences between expenditure in good i by households and production (e.g., changes in the trade balance of good i). Although the households own all firms in the economy, in equilibrium profits are zero due to firms' technology being constant returns to scale.

Firms. Firms are homogeneous within each sector $i \in \mathcal{I}$ and have a technology

$$Y_{it} = A_{it} K_{it}^{\alpha_i} L_{it}^{1-\alpha_i}$$

where A_{it} is the productivity of the firm. They maximize their profits

$$\pi_{it} = p_{it} Y_{it} - \left(1 + \tau_{it}^w\right) w_t L_{it} - \left(1 + \tau_{it}^k\right) R_t K_{it},$$

where $(\tau_{it}^{w}, \tau_{it}^{k})$ are the labor and capital wedges, respectively, and $i = 0$ is the investment sector such that the aggregate capital law of motion is $K_{t+1} = K_t(1-\delta) + Y_{0t}$. The wedges in production input costs are similar to those in Hsieh and Klenow (2009). In Appendix B.1, we consider an extension with production linkages.

4.1.2 Equilibrium

Given initial conditions (capital stock) and an exogenous sequence of sector-level productivities, the competitive equilibrium is defined as the allocations and prices such that (i) the households maximize their utility subject to their budget constraint, (ii) firms maximize profits; and (iii) input and goods markets clear.

4.1.3 Interpretation of Distortions

The formulation of distortions is broad and builds on the business cycle accounting literature (Chari *et al.*, 2007). Distortions related to a firm's input choices—capital and labor distortions—can be interpreted as frictions in capital and labor markets. Changes in capital distortions can reflect, for example, credit supply shocks or changes to credit policies. Similarly, changes in labor distortions can reflect, for example, shifts in labor market regulation, taxation, or market power (see, for example, Ohanian (2009) on labor market distortions during the U.S. Great Depression). In contrast, changes in demand distortions—whether through changes in demand shifters or the expenditure wedge—reflect demand-side frictions, such as shifts in credit access or income taxation, as well as changes in preferences. Frictions can affect sectors differently, leading to heterogeneous distortion dynamics, which can result in the reallocation of resources across sectors, as we show next.[15]

4.2 Model Implications

Next, we derive the relative prices, the demand system, and the reallocation dynamics in equilibrium.

[15]For example, during crises, changes in demand distortions may reflect shifts in demand caused by a sudden reduction in credit, that disproportionately affects sectors such as those producing durable goods (e.g., construction).

4.2.1 Relative Prices

Using the firms' first order conditions we have that the demand for labor and capital are determined by:

$$(1-\alpha_i)\, p_{it} Y_{it} = (1+\tau_{it}^{w})\, w_t L_{it}$$
$$\alpha_i p_{it} Y_{it} = \left(1+\tau_{it}^{k}\right) R_t K_{it}$$

combining the first order conditions we can find

$$p_{it} = \left(\frac{(1+\tau_{it}^{w})\, w_t}{(1+\tau_{it}^{k})\, R_t}\right)^{1-\alpha_i} \frac{(1+\tau_{it}^{k})\, R_t}{A_{it}\,(1-\alpha_i)^{1-\alpha_i}\, \alpha_i^{\alpha_i}}$$

then ratio prices across sectors is

$$\frac{p_{it}}{p_{jt}} = \left(\frac{w_t}{R_t}\right)^{\alpha_j-\alpha_i} \frac{A_{jt}\,(1-\alpha_j)^{1-\alpha_j}\,\alpha_j^{\alpha_j}}{A_{it}\,(1-\alpha_i)^{1-\alpha_i}\,\alpha_i^{\alpha_i}} \left[\frac{(1+\tau_{it}^{w})^{1-\alpha_i}\,(1+\tau_{it}^{k})^{\alpha_i}}{\left(1+\tau_{jt}^{w}\right)^{1-\alpha_j}\,\left(1+\tau_{jt}^{k}\right)^{\alpha_j}}\right]. \tag{3}$$

Relative prices reflect sector-level productivities, production input wedges, and input elasticities across sectors. In Appendix B.1, we show that, with production linkages, relative prices also depend on the network structure, which propagates changes in productivity and distortions.

4.2.2 Demand System

Households' demand for good i is given by

$$c_{it} = \gamma_{it}\left(\frac{(1+\tau_{it}^{c})\, p_{it}}{E_t}\right)^{-\sigma} c_t^{\varepsilon_i(1-\sigma)}$$

where $E_t \equiv \sum_{i\in\mathcal{I}} (1+\tau_{it}^{c})\, p_{it} c_{it}$, such that the expenditure function is

$$E_t\left(c_t, \mathbf{p}_t, \tau_t\right) = \left[\sum_{i\in\mathcal{I}} \gamma_{it}\left((1+\tau_{it}^{c})\, p_{it}\right)^{1-\sigma} c_t^{\varepsilon_i(1-\sigma)}\right]^{\frac{1}{1-\sigma}}.$$

Relative value added across sectors is

$$\frac{\omega_{it}}{\omega_{jt}} = \left(\frac{p_{it}}{p_{jt}}\right)^{1-\sigma} \left(\frac{1+\tau^c_{it}}{1+\tau^c_{jt}}\right)^{-\sigma} \left(\frac{\gamma_{it}}{\gamma_{jt}}\right) c_t^{\left(\varepsilon_i-\varepsilon_j\right)(1-\sigma)}, \tag{4}$$

where $\omega_{it} \equiv p_{it}y_{it}/\sum_{k\in\mathcal{I}} p_{kt}y_{kt}$ is the value-added share of good i. Thus, the allocation of value-added across sectors is determined by relative prices and aggregate consumption, as in standard structural transformation models with non-homothetic preferences, and additionally depends on demand wedges (expenditure wedges and demand shifters).

4.2.3 Reallocation in Equilibrium

Using the firms' labor demands, the relative labor demand across goods in equilibrium is

$$\frac{L_{it}}{L_{jt}} = \frac{\left(1-\alpha_i\right)\omega_{it}}{\left(1-\alpha_j\right)\omega_{jt}} \frac{\left(1+\tau^w_{jt}\right)}{\left(1+\tau^w_{it}\right)}, \tag{5}$$

such that the labor wedges affect the allocation of labor across sectors, explaining the differential dynamics between employment and value-added shares during the crisis. By taking the logarithms of the relative value-added shares equation (4), time-differentiating, and combining this with the relative demand for labor equation (5), we find that

$$\Delta \ln\left(\frac{\omega_{it}}{\omega_{jt}}\right) = \underbrace{(1-\sigma)\,\Delta\ln\left(\frac{p_{it}}{p_{jt}}\right)}_{\text{price}} + \underbrace{\left(\varepsilon_i-\varepsilon_j\right)(1-\sigma)\,\Delta\ln\left(c_t\right)}_{\text{income}} + \underbrace{\Delta\ln\Omega^c_{ijt}}_{D\text{ distortion}} \tag{6}$$

$$\Delta \ln\left(\frac{L_{it}}{L_{jt}}\right) = \Delta\ln\left(\frac{\omega_{it}}{\omega_{jt}}\right) - \underbrace{\Delta\ln\Omega^L_{ijt},}_{L\text{ distortion}} \tag{7}$$

where, given relative prices and aggregate consumption, the demand distortion term $\Omega^c_{ijt} = \frac{\gamma_{it}}{\gamma_{jt}}\left(\frac{1+\tau^c_{it}}{1+\tau^c_{jt}}\right)^{-\sigma}$ summarizes how the demand wedges—demand shifter and expenditure wedge—affect the allocation of economic activity across sectors and the labor distortion term $\Omega^L_{ijt} = \left(\frac{1+\tau^w_{jt}}{1+\tau^w_{it}}\right)^{-1}$ summarizes how labor wedges can distort the relationship between value-added and employment across sectors.

From equations (6) and (7), we can see that the reallocation dynamics of employment and value-added across sectors following a crisis depend on changes in relative prices (*price effect*) and aggregate consumption (*income effect*), which we can approximate directly from the data using aggregate expenditure and price data, combined with standard values of the sectoral income elasticity ε and substitution across sectors σ. Additionally, unobservable changes in labor and demand wedges also play a role. Greater labor distortion will shift employment from one sector to another, and this can be inferred from the observed differential dynamics of value-added and employment across sectors, as highlighted in equation (7). Similarly, the demand distortions can be inferred from the discrepancy between the observed relative value-added dynamics and those predicted solely by income and price effect, see (6).

Distortions and Income and Price Effects. In equilibrium, distortions can generate reallocation through the income effect and relative price changes too. For example, an increase in the average level of distortions that reduces aggregate consumption will induce reallocation via the income effect and, indirectly, via the price effect through changes in wages and the interest rate. Similarly, changes in relative distortions—even if they do not affect aggregate consumption, wages, or the interest rate—will still induce reallocation through changes in relative prices (price effect). From the model, we can infer the dynamics of consumption and labor distortions across sectors, but, a priori, we cannot determine their role through the income and price effects.[16] Therefore, whenever we refer to the role of income and price effects, they may also partially reflect changes in distortions, rather than solely changes in fundamentals, such as productivity.

In the next section, we use the model implications discussed in this section to quantify the contributions of income and price effects, as well as consumption and labor distortions, to post-crisis reallocation.

[16]The only exception is in the version of the model with homogeneous input intensities, where we can identify the role of relative labor distortion changes in driving the price effect.

5 Drivers of Post-Crisis Sectoral Reallocation

In this section, we replicate our empirical analysis using the model simulated data. First, we simulate a version of the model that includes only income and price effects, and compare it to the observed crisis dynamics. Then, we extract the wedges and analyze their dynamics during crises.

Parameters. To simulate the labor and value-added shares we need to assign values to the substitution parameter σ and vector of income elasticites $\{\varepsilon_i\}_{i\in\mathcal{I}}$. We externally calibrate the model using values from Comin *et al.* (2021). We use the manufacturing sector as the base sector.

Table 3: Parameters

	σ	ε_{MAN}	ε_{AGR}	ε_{CON}	$\varepsilon_{\text{SERV}}$
Value	0.1	1	0.32	1.03	1.5*

Notes: *Average of services sectors.
Source: Parameters are from Comin *et al.* (2021), Table XII.

5.1 Reallocation Channels

Now we explore the role of different channels in explaining the reallocation observed during crises.

Income and price effects. First, we use aggregate expenditure and sectoral price data to simulate the dynamics of labor and value-added shares by setting the distortions dynamics to $\Delta \ln \Omega^c_{ijt} = \Delta \ln \Omega^L_{ijt} = 0$.[17] Once we generate the simulated panel of employment and value-added shares for each country over time, we apply the same empirical event analysis model as in our empirical analysis. Figure 4 panel (a) presents the results for value-added and employment relative to the manufacturing sector. The model replicates the value-added dynamics of the agriculture and services sectors relative to manufacturing fairly well, but it fails to account for the relative decline in

[17]We use aggregate real expenditure to approximate aggregate real consumption using national accounts data. Alternatively, Comin *et al.* (2021) use a base sector and total nominal expenditure.

value-added in the construction sector. Additionally, we observe that the value-added and employment dynamics differ. This discrepancy is largely driven by the distinct behavior of value-added and employment in the manufacturing sector during crises, as explained in the empirical section.

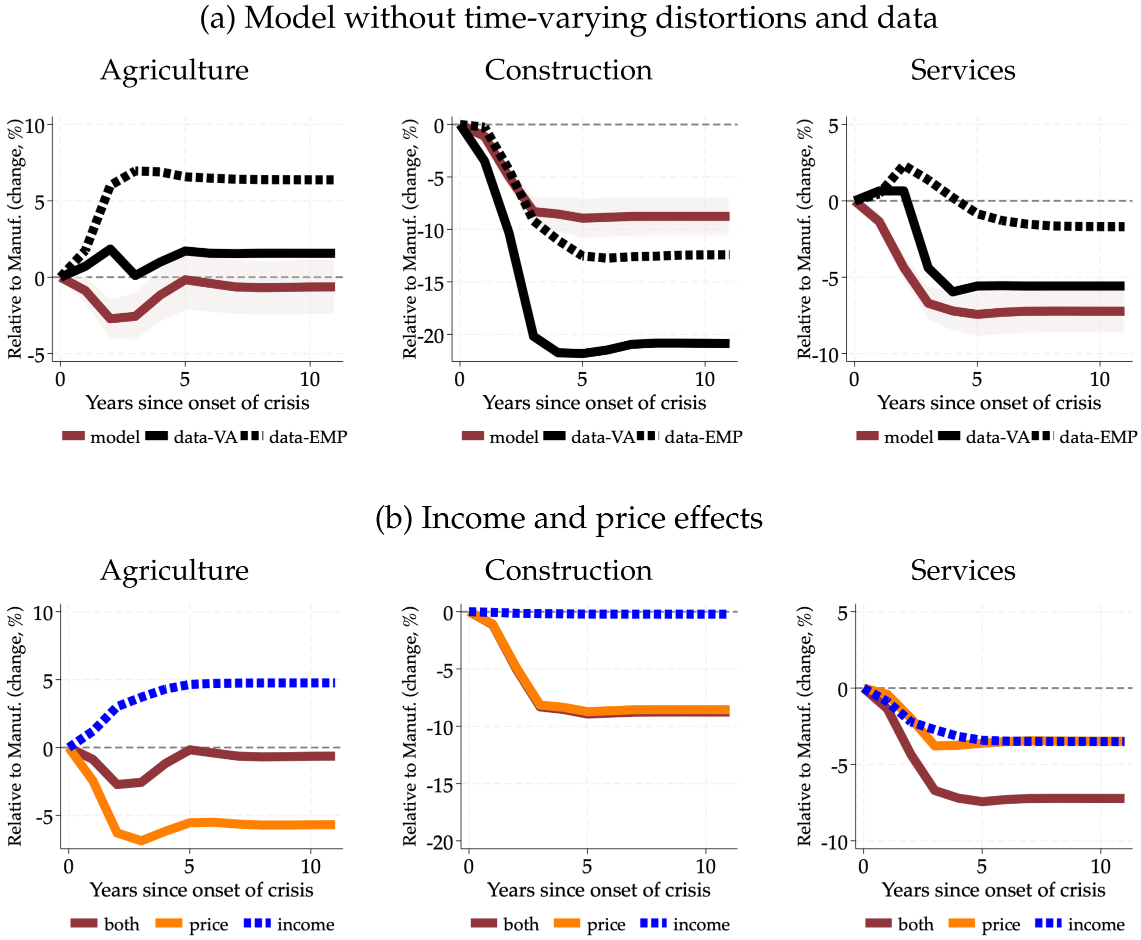
Figure 4 panel (b) shows the dynamics of the income and price effects. Due to a significant contraction in aggregate consumption after crises, we find that the income effect plays an important role in reallocating economic activity from manufacturing to the agriculture sector, to a much lesser extent to construction, and from services to manufacturing. On the other hand, as we observe in the empirical section, relative prices of the manufacturing sector increase relatively more than the rest, which for a $\sigma = 0.1$ elasticity, implies reallocation of economic activity to the manufacturing sector due to the price effect across sectors (i.e., the orange lines are negative for all sectors).

Interestingly, income and price effects roughly offset each other between agriculture and manufacturing. For the reallocation between the construction and manufacturing sectors, the price effect accounts for slightly less than half of the shift out of construction, while the income effect is nearly zero, as the income elasticity of construction relative to manufacturing is close to one. In contrast, for the reallocation between services and manufacturing, both income and price effects drive economic activity out of services and into the manufacturing sector in equal proportions.

Distortions. Figure 5 shows the dynamics of the labor distortions Ω^L_{ijt} and demand distortion Ω^c_{ijt}, between $i = \{\text{AGR}, \text{CON}, \text{SERV}\}$ and $j = \text{MAN}$. First, as expected, labor distortions play a significant role in reallocating labor out of the manufacturing sector and into other sectors, doing so in a highly persistent manner. Interestingly, this result aligns with Chari *et al.* (2007), who find that aggregate labor wedges play a significant role in the Great Depression and the 1982 U.S. recession, and with Cole and Ohanian (2004), who find evidence of large labor distortions in the manufacturing sector during the Great Depression. Our results highlight that these distortions significantly influence reallocation across sectors and are prevalent across multiple countries and crisis episodes.

Next, we find that demand distortions increase in the short run for the agriculture and service sectors but return to near zero after four years. In contrast, demand distortions

Figure 4: Sectoral Reallocation during Crisis: Income and Price Effects



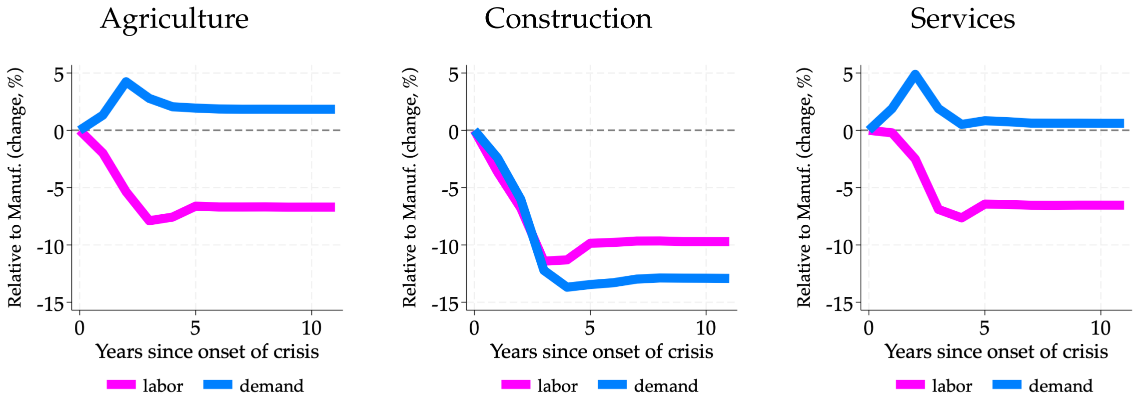
Notes: All variables are relative to the manufacturing sector. Panel (a) shows the dynamics of the relative employment and value added–relative to the manufacturing sector–in model with $\Delta \ln \Omega^c_{ijt} = \Delta \ln \Omega^L_{ijt} = 0$ and in the data. Panel (b) shows the dynamics of the income and relative price components in the crisis. The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

shift economic activity away from the construction sector, suggesting that demand factors may play a relatively more significant role in the construction sector than in the others. These findings align with Müller and Verner (2023), who reports that credit in the construction sector declines significantly more during crises.[18]

Distortions and prices. The previous results regrading distortions shows the extent to which economic activity is reallocated by distortions' changes, given relative prices

[18] In sectors where consumption relies heavily on credit for financing (e.g., durable goods sectors such as construction), a credit crunch would lead to a decrease in expenditure beyond the effects of price and income changes, reflecting a relative increase in demand distortions in our model.

Figure 5: Sectoral Reallocation during Crisis: Distortions



Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of the wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

and aggregate consumption. However, relative prices themselves may also be influenced by distortions. Next, we study how much of the reallocation through relative prices is driven by relative labor distortions. For this we assume capital intensities are the same across sectors and equal to α.[19] In this version of the model, we have that relative price changes are

$$\Delta \ln \left(\frac{p_{it}}{p_{jt}} \right) = \underbrace{\Delta \ln \left(\frac{A_{jt} / \left(1 + \tau^k_{jt}\right)^{\alpha}}{A_{it} / \left(1 + \tau^k_{it}\right)^{\alpha}} \right)}_{\text{productivity + } K \text{ distortion}} + \underbrace{(1 - \alpha)\, \Delta \ln \Omega^L_{ijt}}_{\text{L distortion}}.$$

To explore how distortions can influence reallocation through relative prices, we can use the labor distortions dynamics $\Delta \ln \Omega^L_{ijt}$ that were back-out from the difference between value-added and employment dynamics.[20] In addition, we set $\alpha = 2/3$. Figure A.14 shows that between one-third and one-half of the changes in relative prices—and, consequently, the price effect—are driven by changes in the labor wedge during the crisis. The remainder can be attributed to changes in differential productivity adjusted by capital distortions. Thus, labor distortions contribute both to the divergence between relative value-added and employment dynamics in the manufacturing sector and to

[19]For reference, in absence of heterogeneity in capital intensities relative prices will be simply $\frac{p_{it}}{p_{jt}} = \frac{A_{jt}}{A_{it}} \left(\frac{1+\tau^w_{it}}{1+\tau^w_{jt}} \right)^{1-\alpha} \left(\frac{1+\tau^k_{it}}{1+\tau^k_{jt}} \right)^{\alpha}$.

[20]Note that we do not study the role of relative productivities or capital wedges due to the lack of comprehensive data on sectoral capital that would allow us to observe the productivity shifters A_{jt}/A_{it}.

the reallocation of output toward the manufacturing sector.

5.2 Reallocation Channels: Additional Results

We study the drivers of reallocation across the development spectrum, for different types of crises, and within services sectors.

Emerging vs. Developed. We replicate our baseline analysis separately for emerging and developed economies. For emerging economies, Figure A.15, we find results that closely align with our baseline findings, particularly regarding price and income effects as well as the dynamics of distortions. In contrast, for developed economies, Figure A.16, income and price effects struggle to explain the reallocation from manufacturing to agriculture and to services. Notably, we find a much smaller role for relative employment distortions in driving employment out of manufacturing and a greater role for demand distortions in shifting economic activity toward the agriculture and service sectors. These results highlight the heterogeneity in the drivers of reallocation between crises in emerging and developed economies.

Types of Crisis. Next, we analyze the results separately for crises characterized by large growth reversals, large devaluations, banking crises, and sovereign debt crises. We find that the role of the income and price effects, and distortions are similar across large growth reversals (Figure A.18), large devaluations (Figure A.17), banking crises episodes (Figure A.19), and our baseline set of crises. On the other hand, during sovereign debt crises (Figure A.20) we find a much limited role for labor distortions in the manufacturing sector, particularly relative to agriculture, and we find that demand distortions also play a role in reallocation economic activity out of the service sector. These results suggest that reallocation during sovereign debt crises more clearly aligns with the shift from non-tradable to tradable sectors, than other types of crises, consistent with several papers that study reallocation between these sectors during sovereign debt crises and sudden stops (see, for example, Kehoe and Ruhl (2009); Arellano *et al.* (2018)).

Services. Finally, we extend our analysis to narrower service sectors. For this we use the income elasticities estimated by Comin *et al.* (2021).[21] Figure A.21 shows the results. For all sectors, the income and price effects overstate the extent of reallocation away from them relative to manufacturing. Both effects are of similar magnitude, except in other services sector, where relative prices play a more prominent role. Additionally, we find that labor distortions have a comparable impact across sectors in reallocating labor out of manufacturing, except in transportation, where relative labor distortions are negligible. Finally, demand distortions exhibit a moderate and similar dynamics across service sectors. Overall, despite a significantly larger reallocation out of finance and real estate (approximately twice as large), the dynamics of income and price effects, as well as distortions, remain broadly similar across sectors.

6 Conclusions

Do crises shape the economic structure? Yes. Our findings reveal significant and persistent sectoral reallocation following a crisis. Crises tend to shift resources toward the agriculture sector, delaying structural transformation, while having a limited impact on reallocation out of the service sector. Income effects and relative prices across sectors effectively explain the post-crisis dynamics of output reallocation for all sectors except construction, which collapses during crises due to increased demand distortions in this sector. Additionally, although output shifts to manufacturing, as predicted by income and price effects, there is minimal employment reallocation to this sector, resulting in increased labor distortions in manufacturing relative to other sectors.

The paper remains silent on the mechanisms driving the heterogeneous changes in labor and demand distortions across sectors after a crisis. Why are these changes so persistent? Are the sectoral dynamics driven by persistent policy changes, such as changes in regulations or taxes, that affect sectors differently? Or are they the result of interactions between fundamental shocks and preexisting market frictions that can lead the economy to a new equilibrium? These questions are left for future work.

[21] We use the estimates from Table XII in Comin *et al.* (2021) that are consistent with the sectors in our paper. The values are $\varepsilon_{\text{WRT}} = 1.62$ for wholesale and retail, $\varepsilon_{\text{TRA}} = 1.44$ for transport, storage, and communications, $\varepsilon_{\text{FIRE}} = 2.17$ for finance, insurance, and real estate, and $\varepsilon_{\text{OTH}} = 1.18$ for personal and other services.

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A Data Appendix

Table A.1: List of Countries in Baseline Sample

Code	Category	Country	Period	Crisis
ARG	Emerging	Argentina	1950-2018	1951,1956,1980,1989,1995,2001,2014
AUS	Developed	Australia	1984-2018	
AUT	Developed	Austria	1970-2019	2008
BEL	Developed	Belgium	1970-2019	2008
BFA	Emerging	Burkina Faso	1965-2018	1990
BGD	Emerging	Bangladesh	1990-2018	
BGR	Emerging	Bulgaria	1995-2019	1996
BOL	Emerging	Bolivia	1950-2018	1980,1986,1994
BRA	Emerging	Brazil	1950-2018	1961,1983,1990
CAN	Developed	Canada	1970-2019	
CHE	Developed	Switzerland	1991-2018	2008
CHL	Emerging	Chile	1950-2018	1961,1976,1981
CHN	Emerging	China	1952-2018	1998
CMR	Emerging	Cameroon	1965-2018	1987,1995
COL	Emerging	Colombia	1950-2018	1982,1998
CRI	Emerging	Costa Rica	1950-2018	1962,1981,1987,1994
CZE	Developed	Czech Republic	1995-2019	1996
DEU	Developed	Germany	1970-2019	2008
DNK	Developed	Denmark	1948-2019	2008
ECU	Emerging	Ecuador	1990-2018	1998,2008
EGY	Emerging	Egypt	1960-2018	1980
ESP	Developed	Spain	1956-2019	1977,2008
ETH	Emerging	Ethiopia	1961-2018	
FIN	Developed	Finland	1970-2019	1991
FRA	Developed	France	1954-2019	2008
GBR	Developed	United Kingdom	1948-2019	2007
GHA	Emerging	Ghana	1960-2018	1966,1982
GRC	Developed	Greece	1970-2019	2008
HKG	Developed	Hong Kong	1970-2018	
HRV	Emerging	Croatia	1995-2019	1998
HUN	Emerging	Hungary	1991-2019	1991,2008
IDN	Emerging	Indonesia	1966-2018	1966,1997
IND	Emerging	India	1950-2018	1958,1969,1993
IRL	Developed	Ireland	1970-2019	2008
ISR	Developed	Israel	1990-2018	
ITA	Developed	Italy	1951-2019	2008
JPN	Developed	Japan	1953-2018	1997
KEN	Emerging	Kenya	1960-2018	1985,1992
KHM	Emerging	Cambodia	1990-2018	
KOR	Developed	South Korea	1953-2018	1997
LAO	Emerging	Laos	1990-2018	
LKA	Emerging	Sri Lanka	1990-2018	
LSO	Emerging	Lesotho	1964-2018	
LTU	Emerging	Lithuania	1995-2019	1995
LVA	Emerging	Latvia	1995-2019	1995,2008

Notes: Table shows the countries in our baseline sample. The period refers to the data coverage period. Crisis refers to the dates that a crisis episode happens.

Table A.2: List of Countries in Baseline Sample (cont.)

Code	Category	Country	Period	Crisis
MAR	Emerging	Morocco	1960-2018	1980
MEX	Emerging	Mexico	1950-2018	1981,1994
MMR	Emerging	Myanmar	1990-2018	
MOZ	Emerging	Mozambique	1966-2018	1984
MWI	Emerging	Malawi	1960-2018	1982
MYS	Emerging	Malaysia	1970-2018	1997
NGA	Emerging	Nigeria	1960-2018	1983,1991,2009
NLD	Developed	Netherlands	1959-2019	2008
NOR	Developed	Norway	1970-2018	1991
NPL	Emerging	Nepal	1990-2018	
NZL	Developed	New Zealand	1971-2018	
PAK	Emerging	Pakistan	1990-2018	
PER	Emerging	Peru	1950-2018	1969,1978,1983
PHL	Emerging	Philippines	1971-2018	1983,1997
PRT	Developed	Portugal	1970-2019	2008
ROU	Emerging	Romania	1995-2019	1998
RWA	Emerging	Rwanda	1966-2018	
SEN	Emerging	Senegal	1960-2018	1981,1988
SGP	Developed	Singapore	1970-2018	
SVK	Emerging	Slovakia	1995-2019	1998
SVN	Developed	Slovenia	1995-2019	2008
SWE	Developed	Sweden	1960-2019	1991,2008
THA	Emerging	Thailand	1951-2018	1983,1997
TUN	Emerging	Tunisia	1990-2018	1991
TUR	Emerging	Turkey	1990-2018	2000
TWN	Emerging	Taiwan	1951-2018	1983,1995
TZA	Emerging	Tanzania	1960-2018	1984
UGA	Emerging	Uganda	1955-2018	1981,1994
USA	Developed	United States	1947-2019	1988,2007
VEN	Emerging	Venezuela	1950-2012	1982,1994
VNM	Emerging	Vietnam	1990-2018	1997
ZAF	Emerging	South Africa	1960-2018	1985
ZMB	Emerging	Zambia	1960-2018	1983,1995

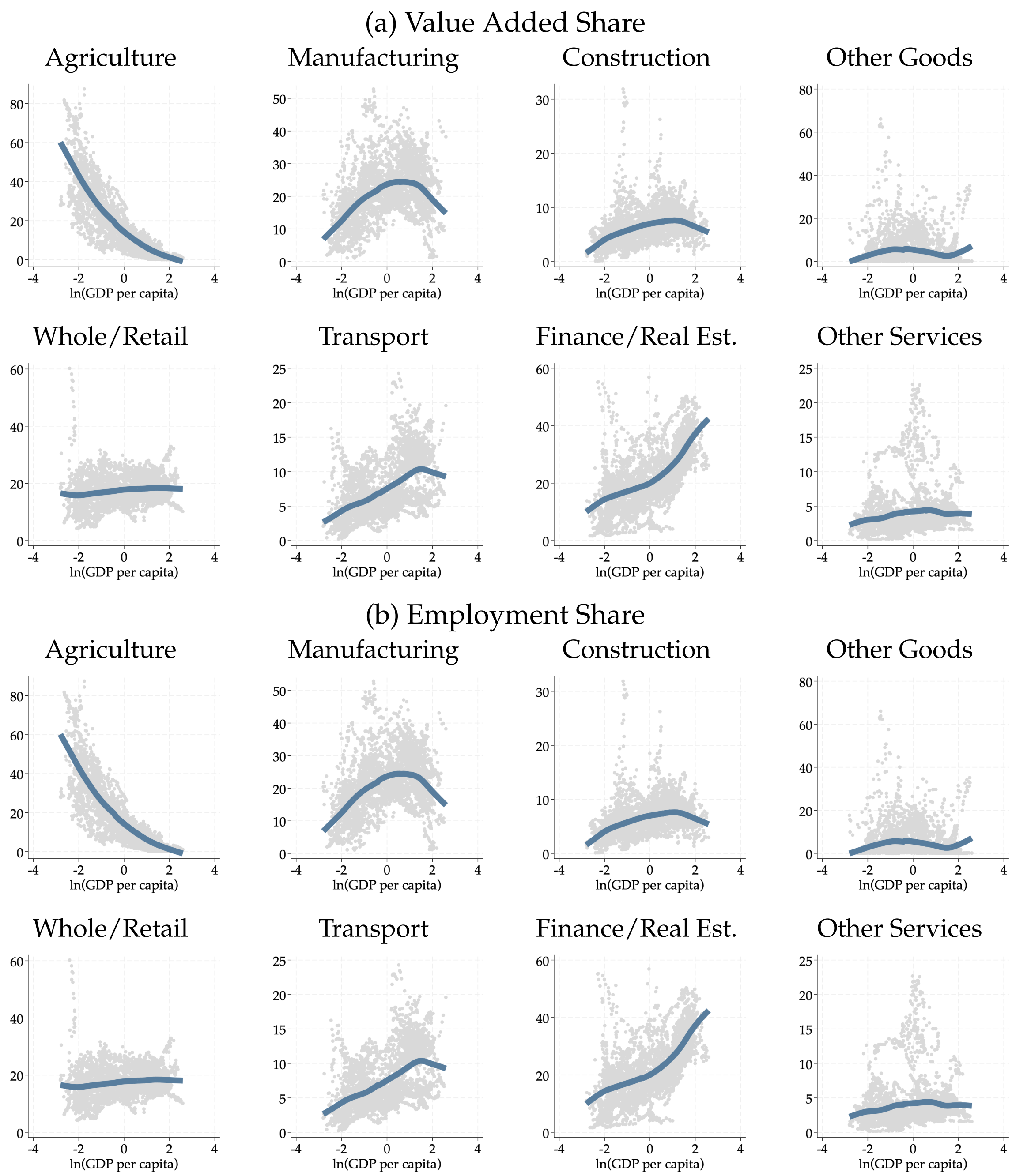
Notes: Table shows the countries in our baseline sample. The period refers to the data coverage period. Crisis refers to the dates that a crisis episode happens.

Table A.3: Sectoral Shares Distribution: Disaggregated Sectors

	Employment				Value Added			
	Mean	P25	P50	P75	Mean	P25	P50	P75
a. All								
Goods	60	43	59	77	49	40	49	58
Agriculture	36	9	28	60	16	4	11	25
Construction	7	3	7	9	7	5	7	8
Manufacturing	17	10	16	23	22	16	22	27
Other Goods	1	0	0	1	4	1	2	5
Services	40	23	41	57	51	42	51	60
Wholesale/Retail Trade	19	12	20	25	18	15	17	21
Transport	6	3	5	9	8	5	7	11
Finance and Real Estate	9	2	6	13	22	15	21	28
Other Services	7	4	6	8	4	2	3	4
b. Crisis Window								
Goods	59	42	59	77	49	40	51	58
Agriculture	35	11	28	60	15	5	11	21
Construction	7	4	7	9	6	4	6	8
Manufacturing	17	12	16	22	23	17	22	27
Other Goods	1	0	0	1	5	1	2	6
Services	41	23	41	58	51	42	49	60
Wholesale/Retail Trade	18	12	19	24	17	15	17	20
Transport	6	3	6	9	8	5	6	11
Finance and Real Estate	8	2	5	13	22	16	21	28
Other Services	8	5	7	10	4	3	3	5

Notes: Table shows the value added and employment shares for each sector. Panel (a) shows for all the sample, and Panel (b) the values around crisis. Services includes wholesale and retail trade, transportation, finance and real estate activities, and other services. Other goods includes mining.
Data source: Penn World Tables, and Groningen Growth and Development Center.

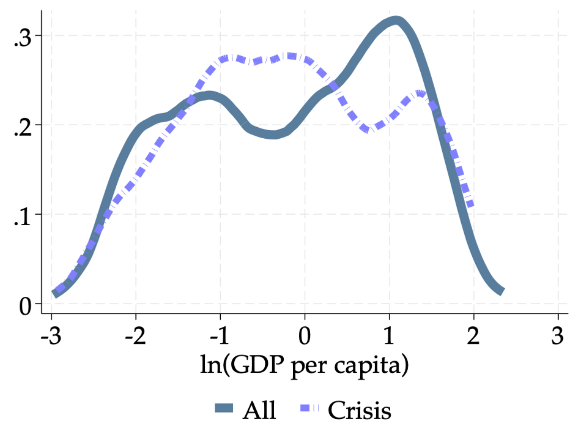
Figure A.1: Structural Transformation: Disagregated Sectors



Notes: The figure shows the share of value added and employment across the level of income, measure in terms of log GDP per capita PPP. The log GDP is normalized by 0 relative to the sample's median. Each point is a country-year observation and the solid lines are the locally weighted smoothing of observed shares.

Data source: Penn World Tables, and Groningen Growth and Development Center.

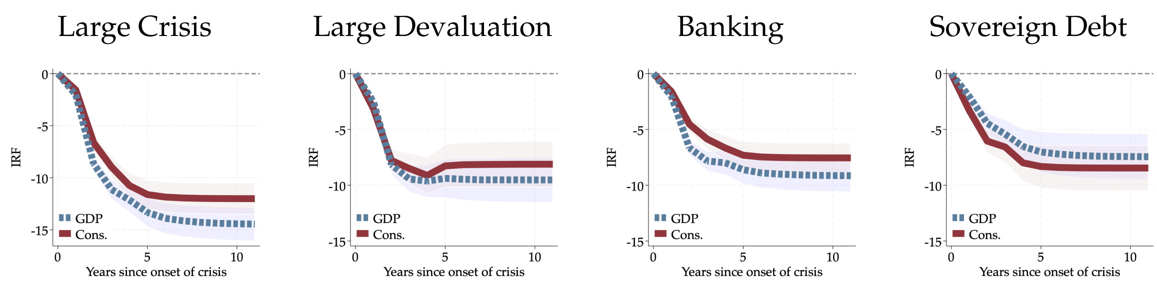
Figure A.2: Output per Capita Distribution



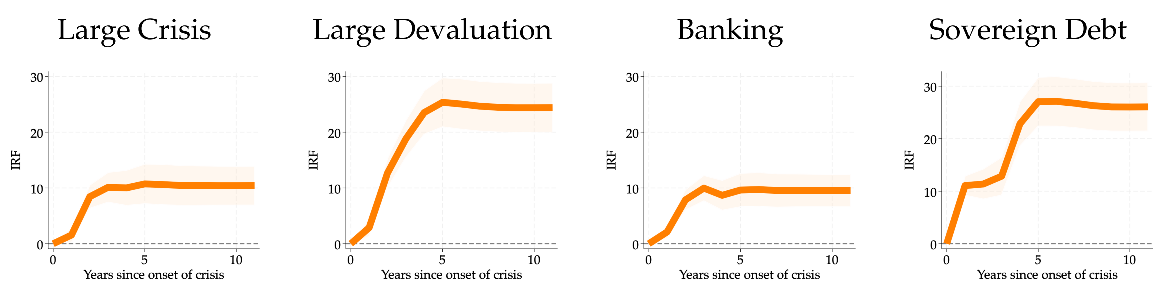
Notes: The Figure shows the distribution of the log GDP per capita PPP for all the observations in our baseline sample, around a banking crisis, and around a sovereign debt crisis. The log GDP is normalized by 0 relative to the sample's median. The windows around the crisis are defined between the two years before and two years after the onset of the crisis. Data source: Penn World Tables and baseline crisis episodes.

Figure A.3: Macro Dynamics During Crises: Other Types

(a) Aggregate Output and Consumption

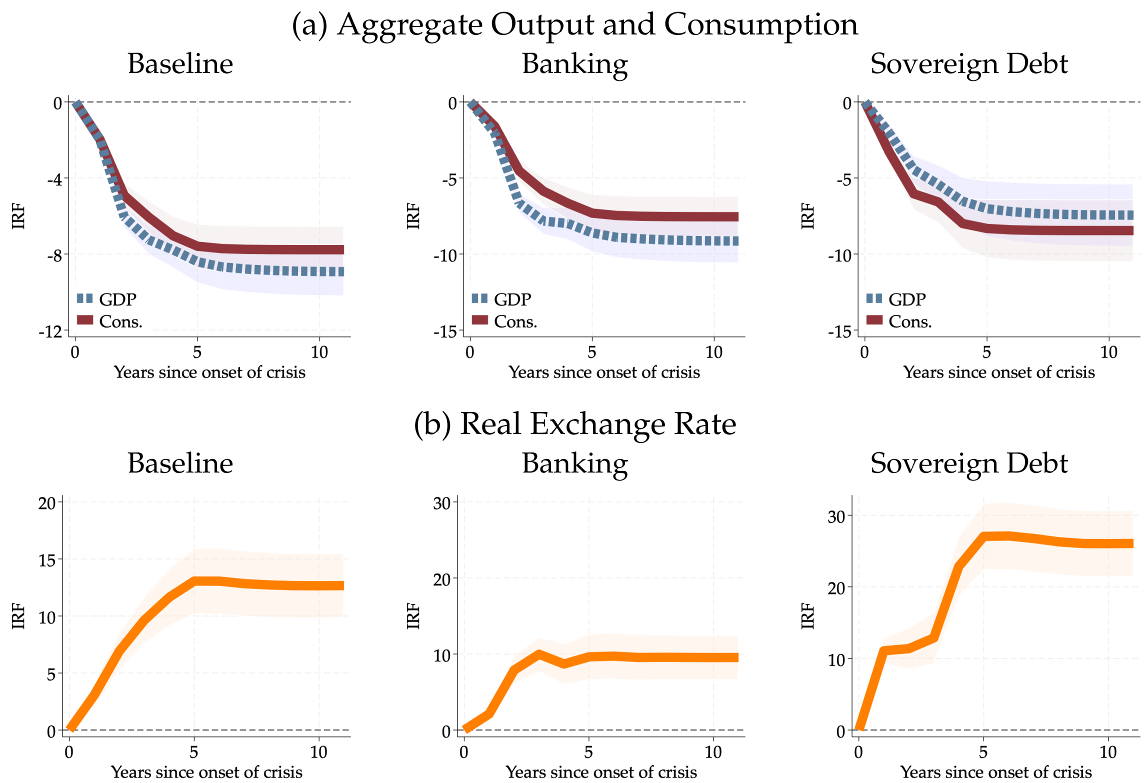


(b) Real Exchange Rate



Notes: The Figure shows the IRF of aggregate real output per capita (GDP), consumption per capita (Cons.), and the real exchange (REER) for the episode with large GDP growth reversals, episodes with large devaluations, banking crises, and sovereign debt crises using empirical model (1). The impulse response shows the estimated percentage point impact on real GDP from a crisis using the estimated coefficients. The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. Further details regarding the sectoral data and crisis episodes definitions are in Section 2.
Data sources: described in Section 2.1.

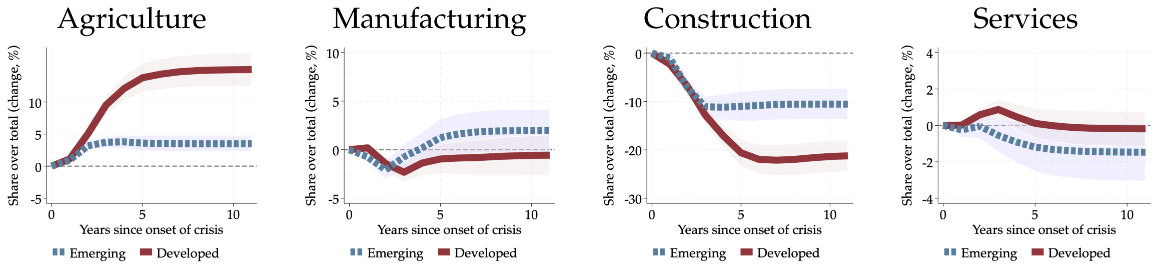
Figure A.4: Macro Dynamics During Crises: Banking and Sovereign Debt



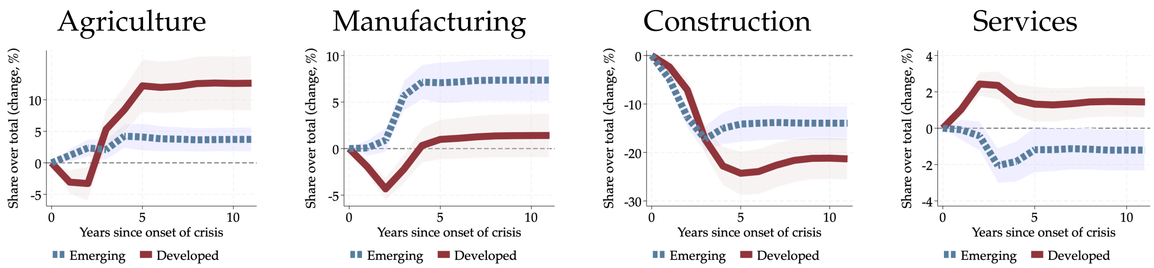
Notes: The Figure shows the IRF of aggregate real output per capita (GDP), consumption per capita (C), and the real exchange (REER) for the baseline crisis episodes, banking crisis, and sovereign debt crisis using the model: $g_{it} = \alpha_i + \sum_{j=1}^{4} \beta_j g_{it-j} + \sum_{s=1}^{4} \gamma_s D_{it-s} + \varepsilon_{it}$ for country i in year t where α_i is a country fixed effect, g_{it} is the percentage change in real GDP/C/REER, and D_{it} is a dummy variable indicating the first year of a crisis. The impulse response shows the estimated percentage point impact on real GDP from a crisis using the estimated coefficients. The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. Further details regarding the sectoral data and crisis episodes definitions are in Section 2.
Data sources: described in Section 2.1.

Figure A.5: Sectoral Reallocation during Crisis: Emerging vs Developed

(a) Employment



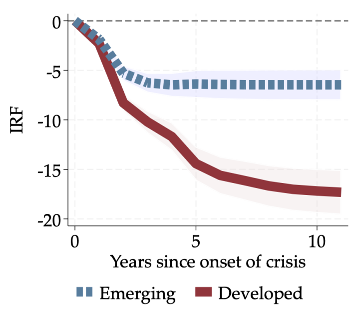
(b) Value Added



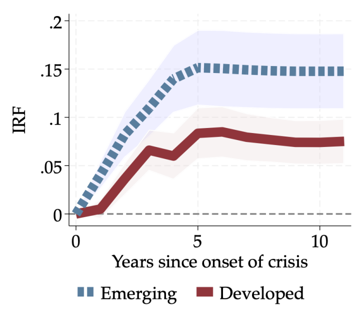
Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using the model (2) for Emerging and Developed Economies. The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.6: Macro Dynamics During Crises: Emerging vs Developed

(a) Aggregate Output

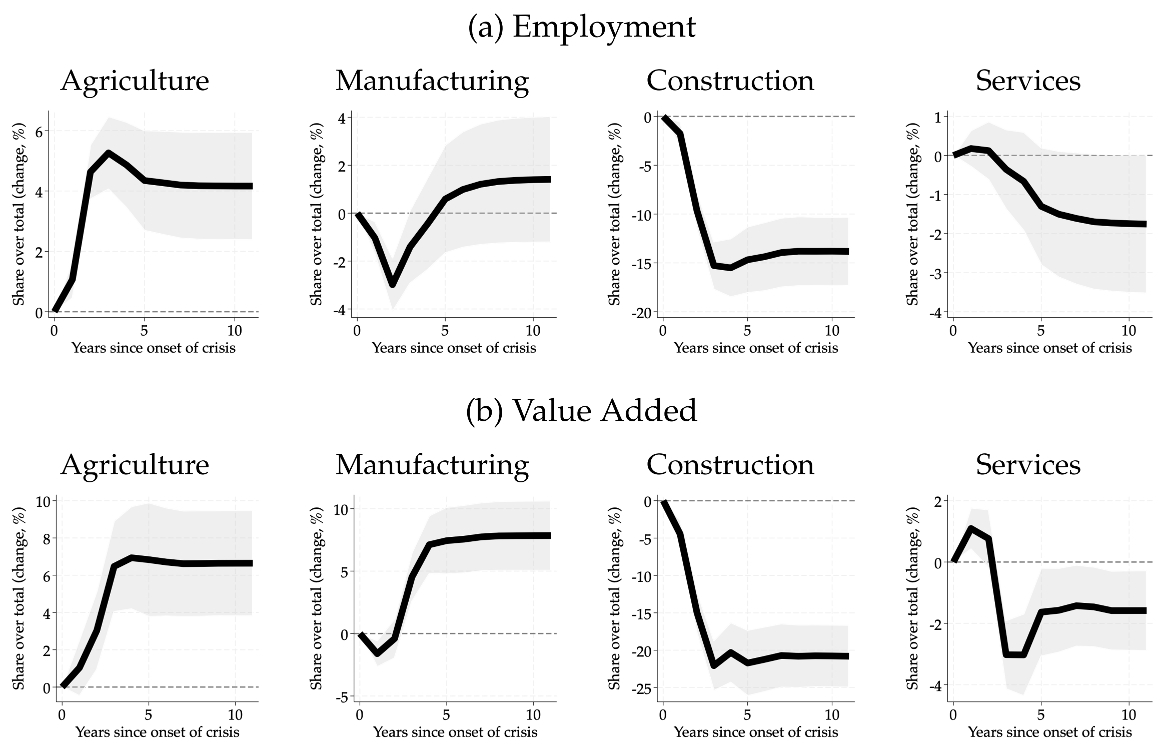


(b) Real Exchange Rate



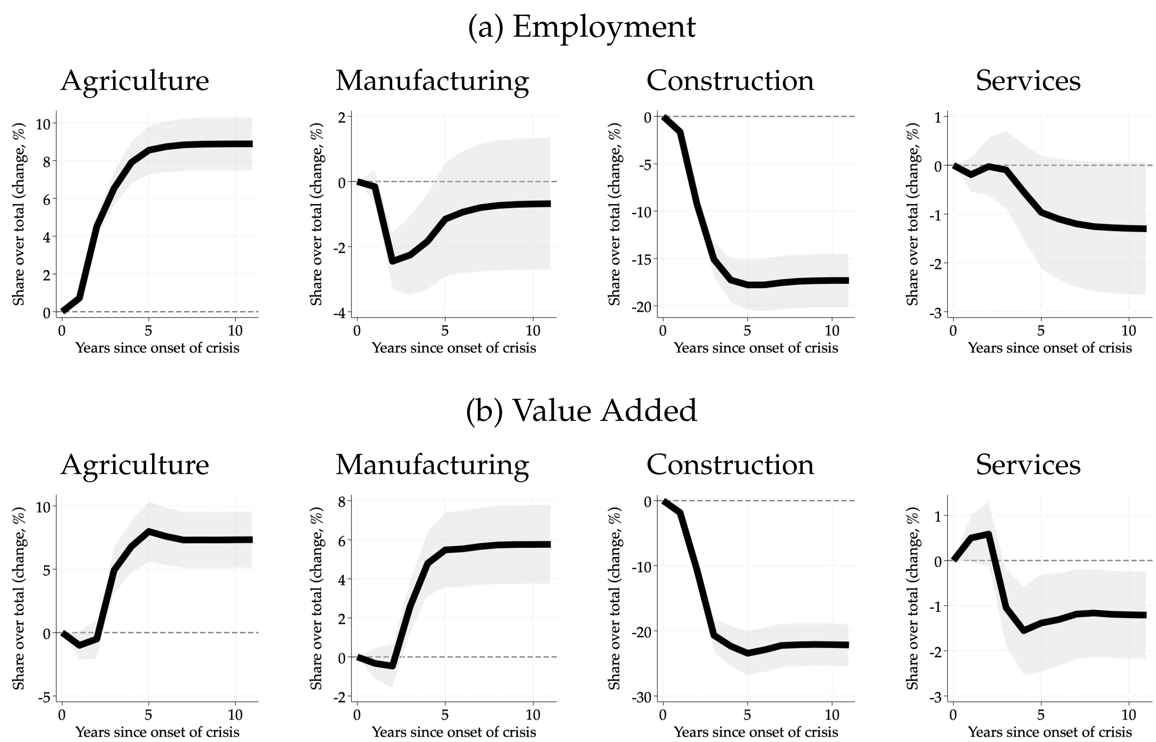
Notes: The Figure shows the IRF of aggregate real output per capita (GDP), and the real exchange (REER) for the baseline crisis episodes for emerging and developed economies: $g_{it} = \alpha_i + \sum_{j=1}^{4} \beta_j g_{it-j} + \sum_{s=1}^{4} \gamma_s D_{it-s} + \varepsilon_{it}$ for country i in year t where α_i is a country fixed effect, g_{it} is the percentage change in real GDP/C/REER, and D_{it} is a dummy variable indicating the first year of a crisis. The impulse response shows the estimated percentage point impact on real GDP from a crisis using the estimated coefficients. The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. Further details regarding the sectoral data and crisis episodes definitions are in Section 2.
Data sources: described in Section 2.1.

Figure A.7: Sectoral Reallocation during Crisis: Large Devaluation



Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using the model (2). The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Crisis episodes are banking and/or sovereign default episodes with large devaluations. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

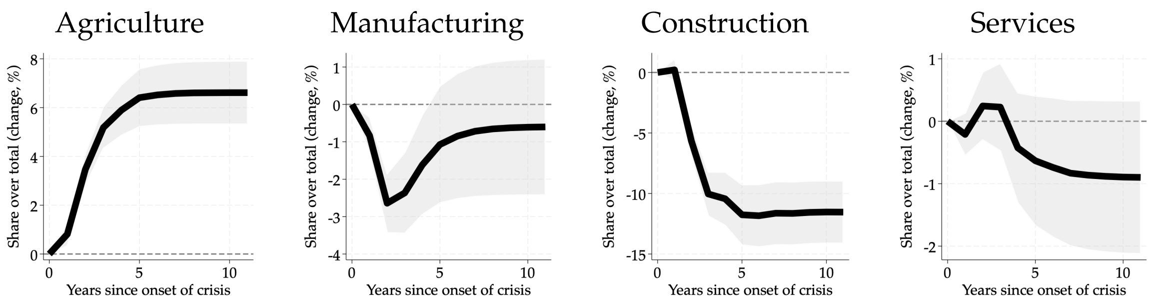
Figure A.8: Sectoral Reallocation during Crisis: Large Growth Reversal



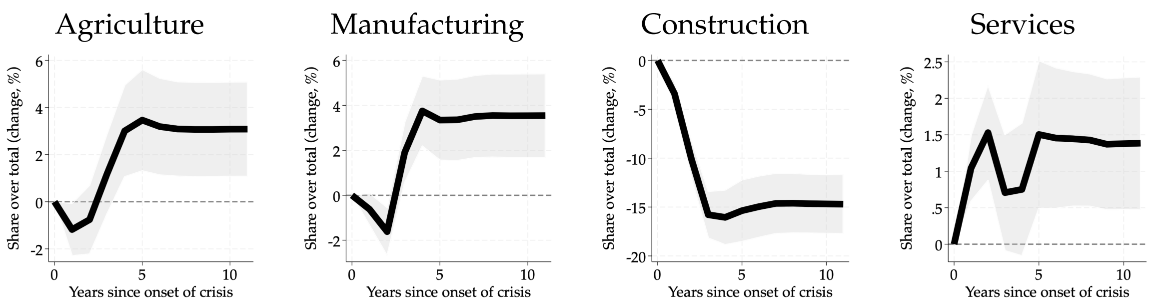
Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using the model (2). The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Crisis episodes are banking and/or sovereign default episodes with large growth reversals. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.9: Sectoral Reallocation during Crisis: Banking Crisis

(a) Employment

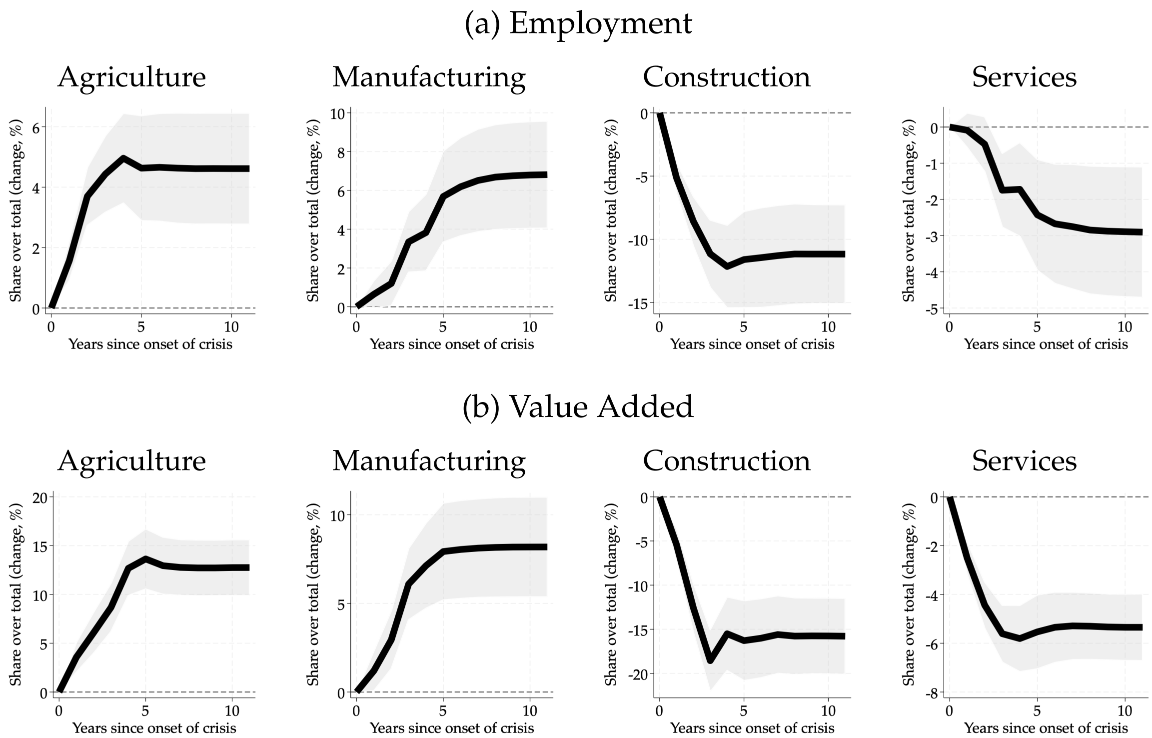


(b) Value Added



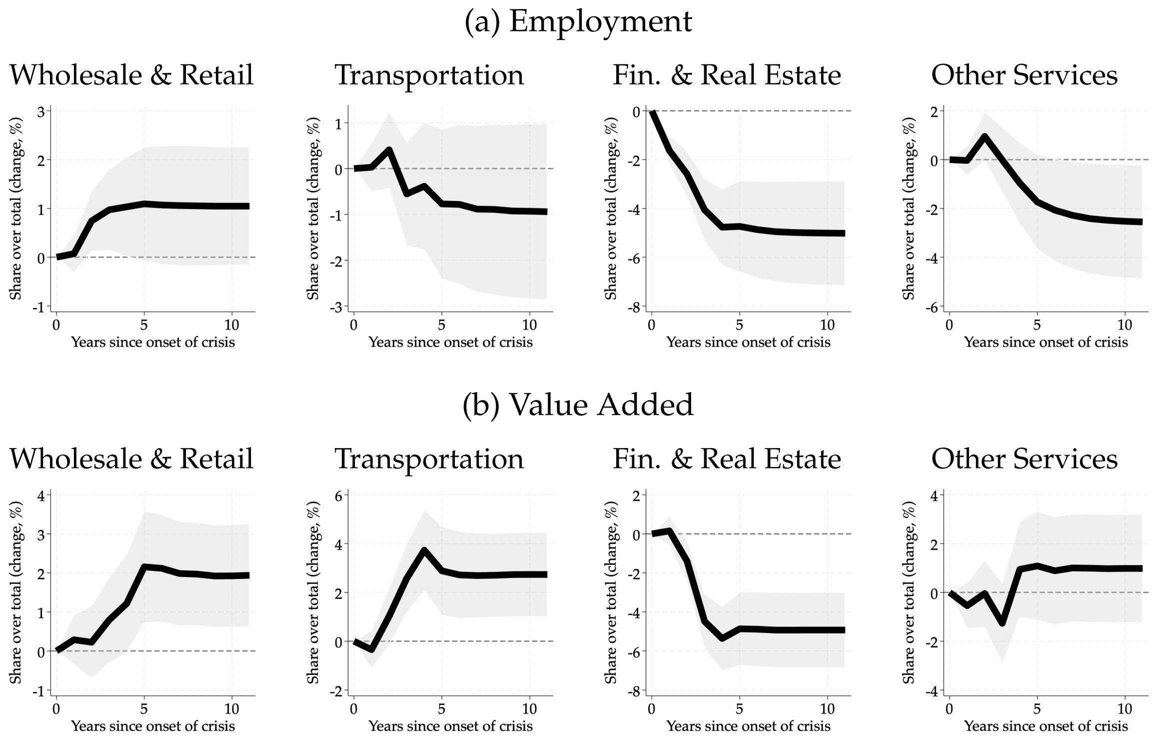
Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using the model (2). The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Crisis episodes are banking crisis. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.10: Sectoral Reallocation during Crisis: Sovereign Default



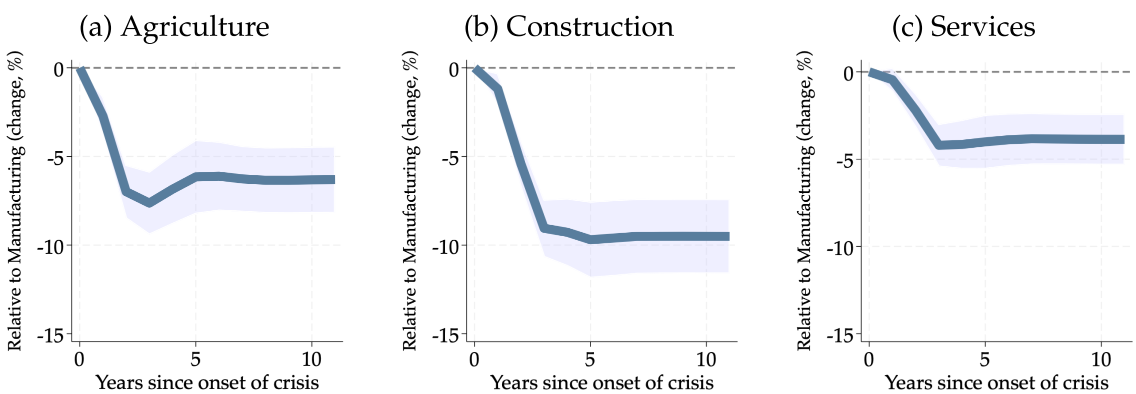
Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using the model (2). The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Crisis episodes are sovereign default episodes. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.11: Sectoral Reallocation during Crisis: Disaggregate Service Sectors



Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using the model (2). The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

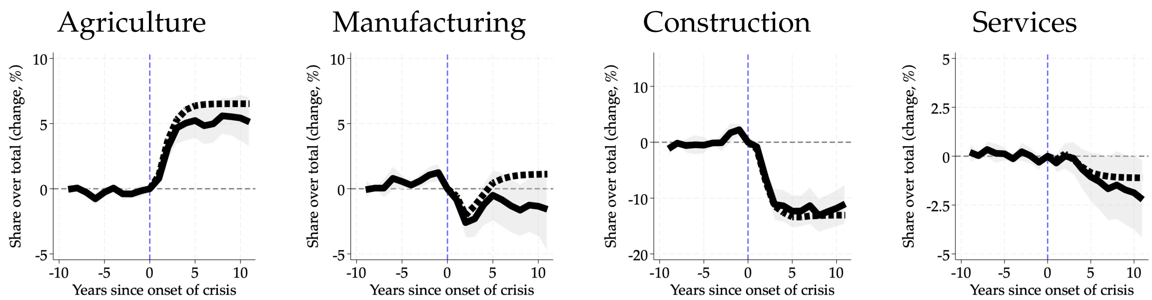
Figure A.12: Sectoral Prices Dynamics during Crisis: Prices Relative to Manufacturing



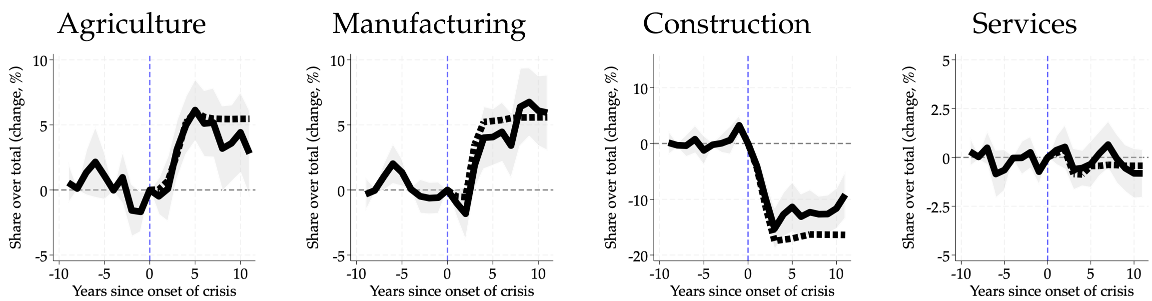
Notes: The Figure shows the IRF of the sectoral prices, relative to the manufacturing sector prices, estimated using the model (2). The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.13: Sectoral Reallocation during Crisis: Local Projections

(a) Employment

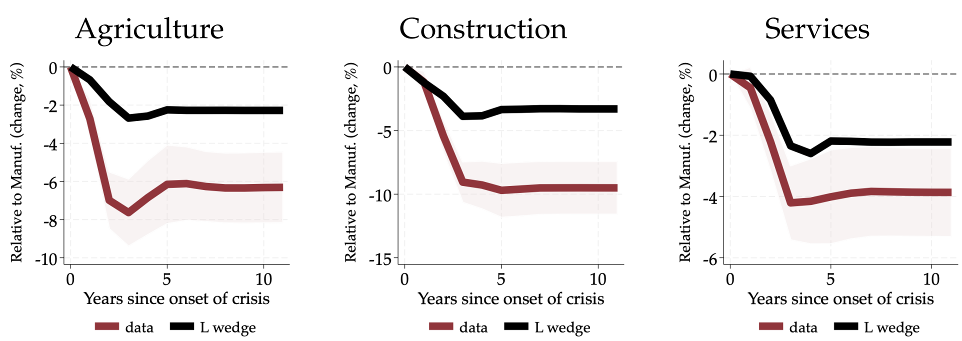


(b) Value Added



Notes: The Figure shows the IRF of the employment share (panel a) and value added shares (panel b) estimated using local projections (solid line) and using the baseline empirical model (dashed line). We estimate $\ln s^k_{it+h} - \ln s^k_{it} = \alpha^{kh}_i + \beta^{kh} D_{it+1} + \gamma^{kh} \mathbf{Z}_{it} + \varepsilon^{kh}_{it+h}$, where s^k_{it} is the employment/value-added share at period t for country i and sector k, D_{it+1} indicates the first period of the crisis, α^{kh}_i is a country fixed effect, and $\mathbf{Z}_{it}$ are control variables. We control by the level of income and sectoral share before the crisis. The coefficient β^{kh} calculates the dynamic of the sector h periods after the crisis for sector k. We estimate for $h \in [-10, 10]$. Further details regarding the data are in Section 2.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

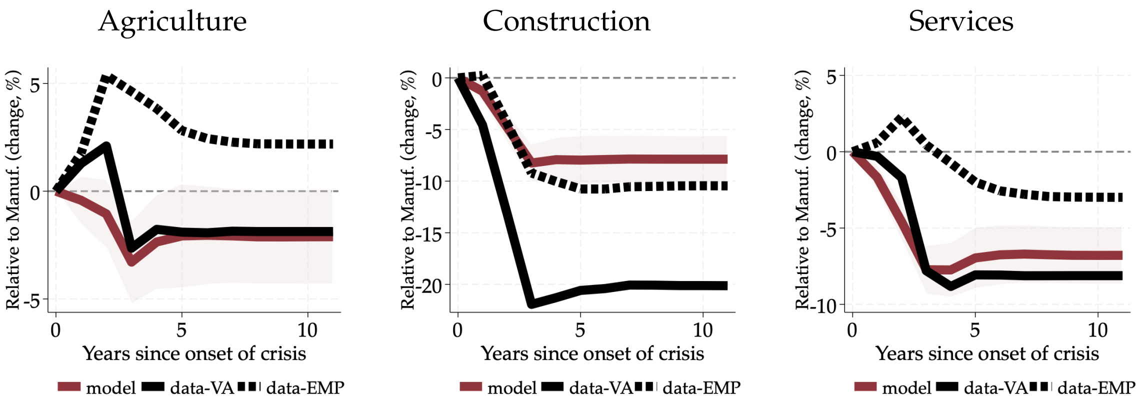
Figure A.14: Sectoral Reallocation during Crisis: Distortions and Relative Prices



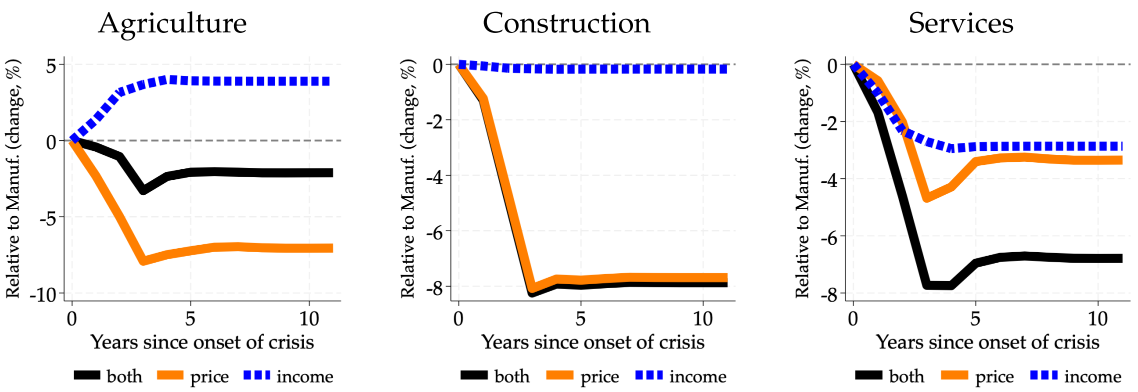
Notes: All variables are relative to the manufacturing sector. The figures shows the observed dynamics of the relative prices and the predicted change in relative prices due to labor wedges changes. For the empirical model, we fix $H = J = 4$. The shadow indicates the one standard deviation error band computed from 1,000 Monte Carlo simulations using the variance-covariance matrix of the estimated coefficients and their asymptotically normal distribution. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.15: Sectoral Reallocation during Crisis: Emerging Economies

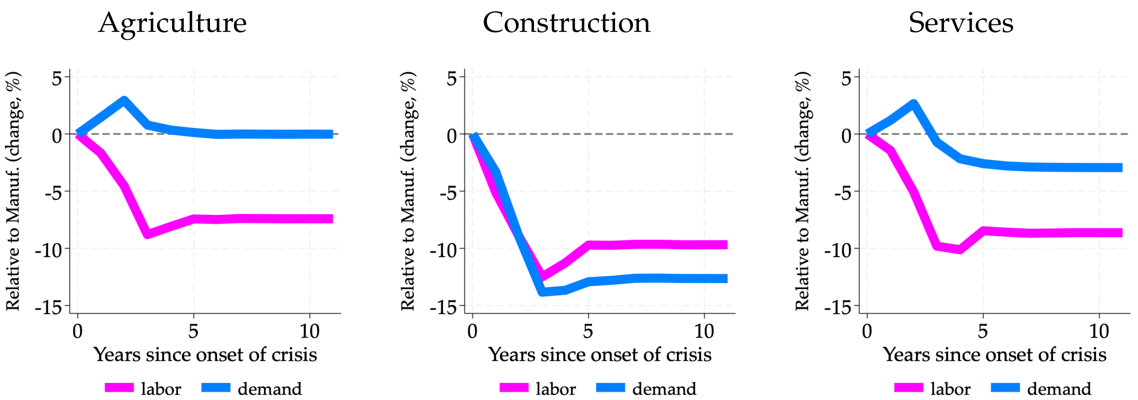
(a) Model without time-varying distortions and data



(b) Income and price effects



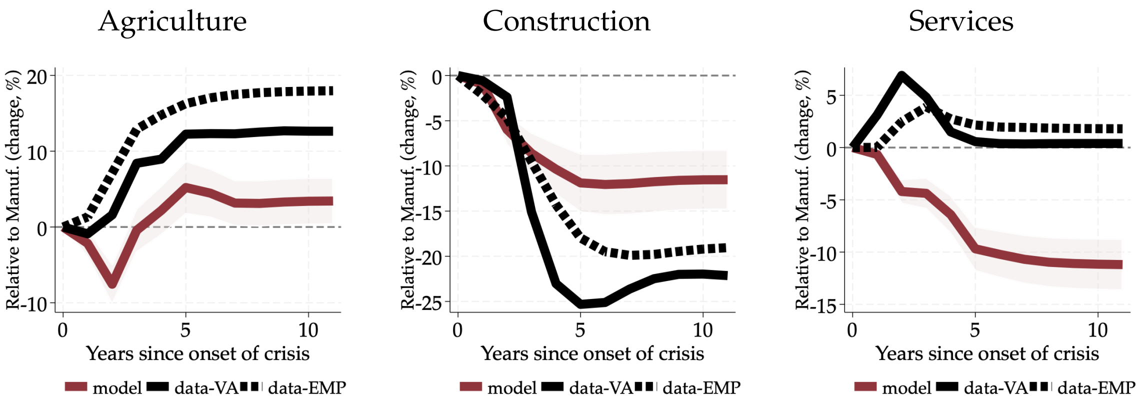
(c) Distortions



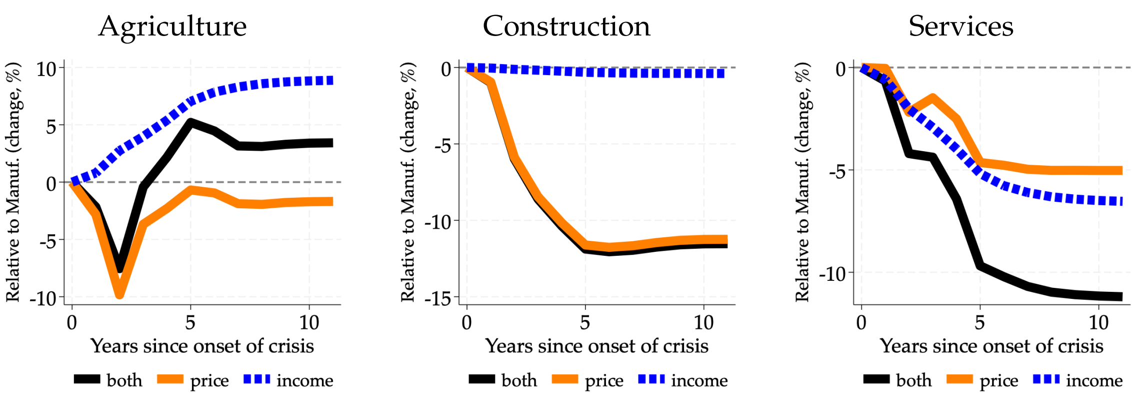
Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of sectoral reallocation and wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.16: Sectoral Reallocation during Crisis: Developed Economies

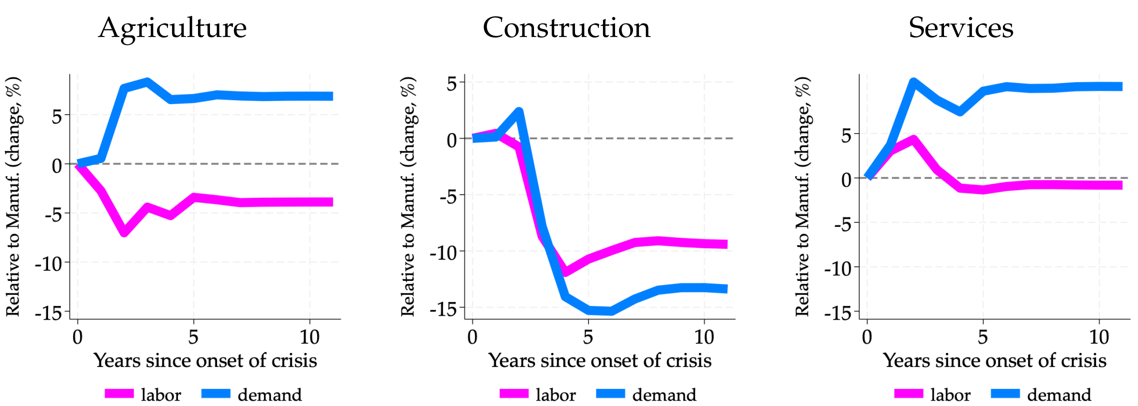
(a) Model without time-varying distortions and data



(b) Income and price effects

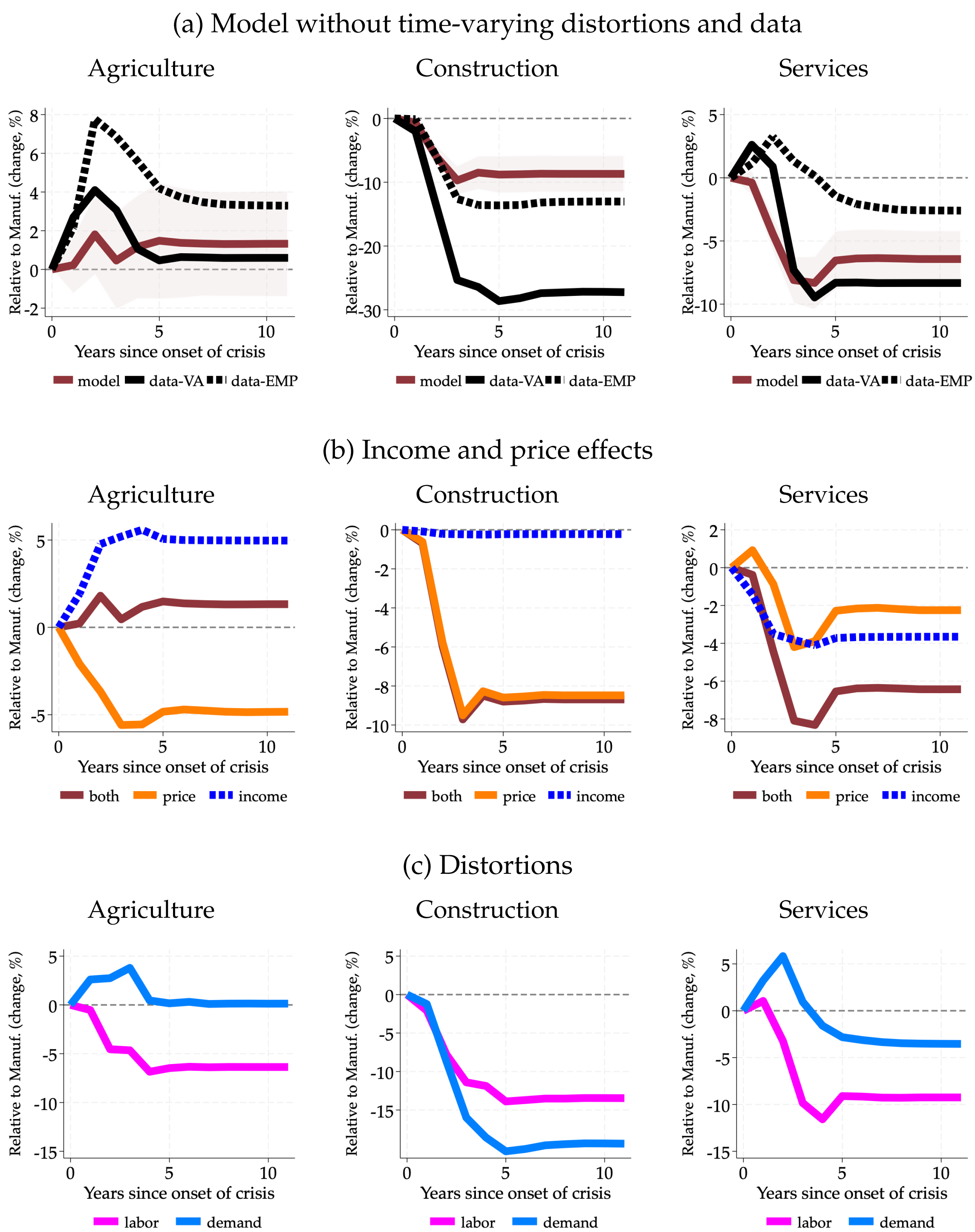


(c) Distortions



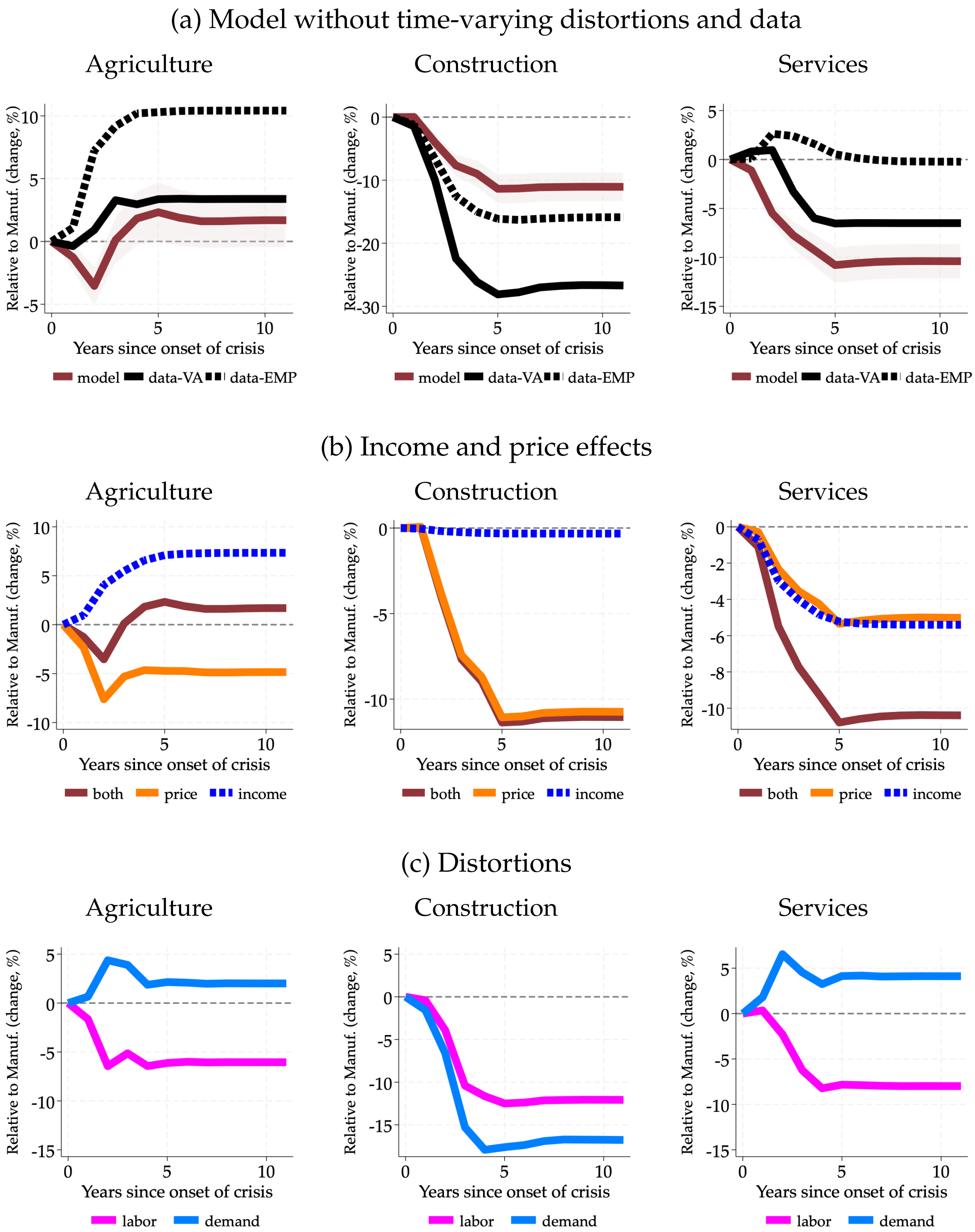
Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of sectoral reallocation and wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.17: Sectoral Reallocation during Crisis: Large Devaluations



Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of sectoral reallocation and wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

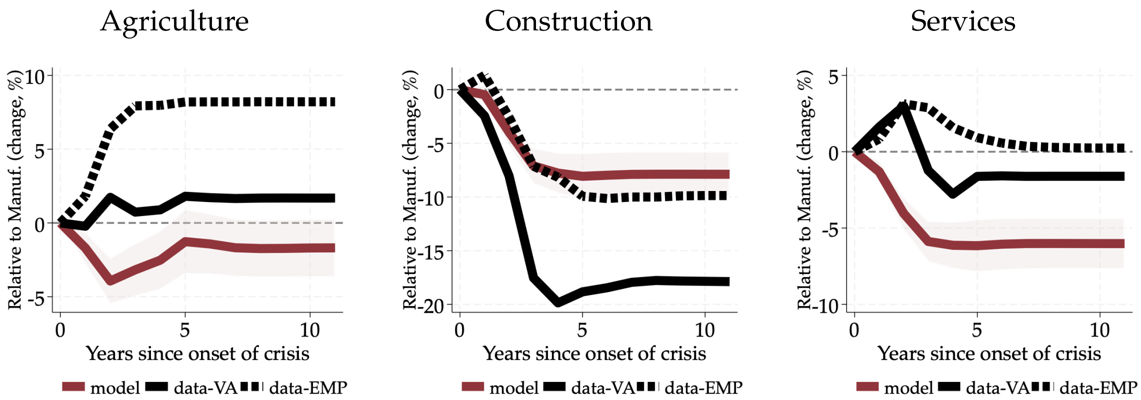
Figure A.18: Sectoral Reallocation during Crisis: Large Growth Reversal



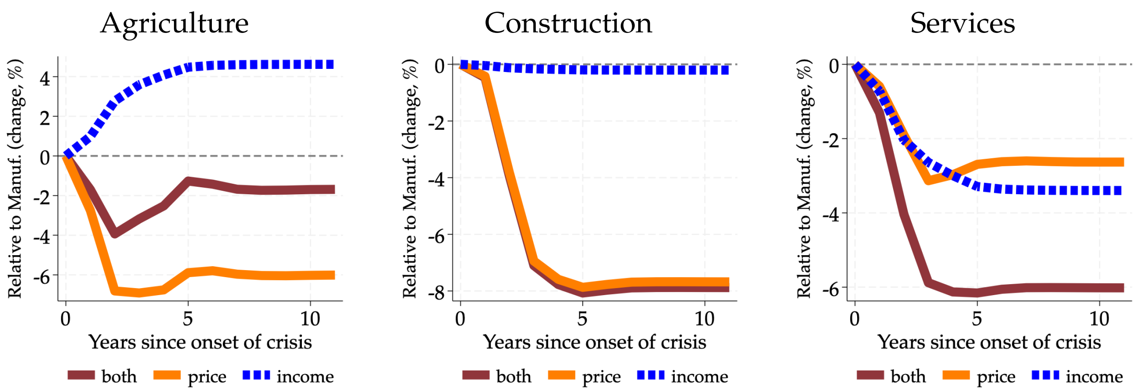
Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of sectoral reallocation and wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.19: Sectoral Reallocation during Crisis: Banking Crisis

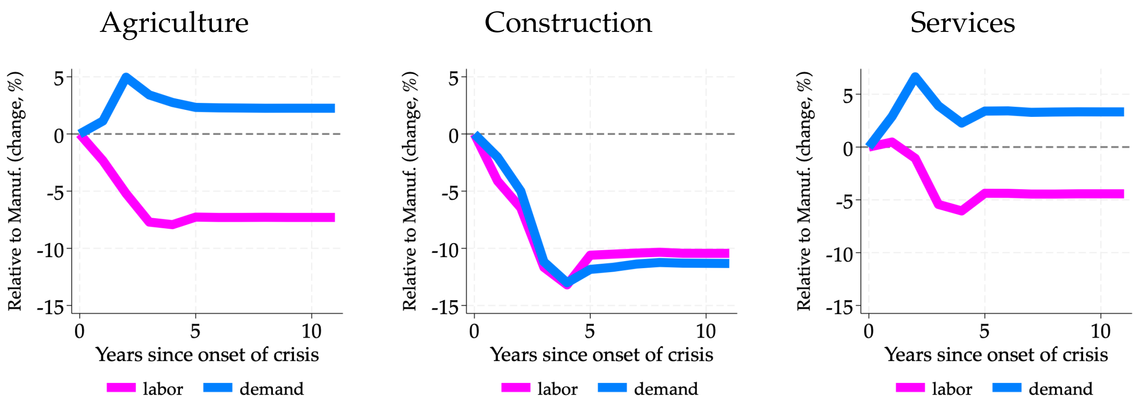
(a) Model without time-varying distortions and data



(b) Income and price effects

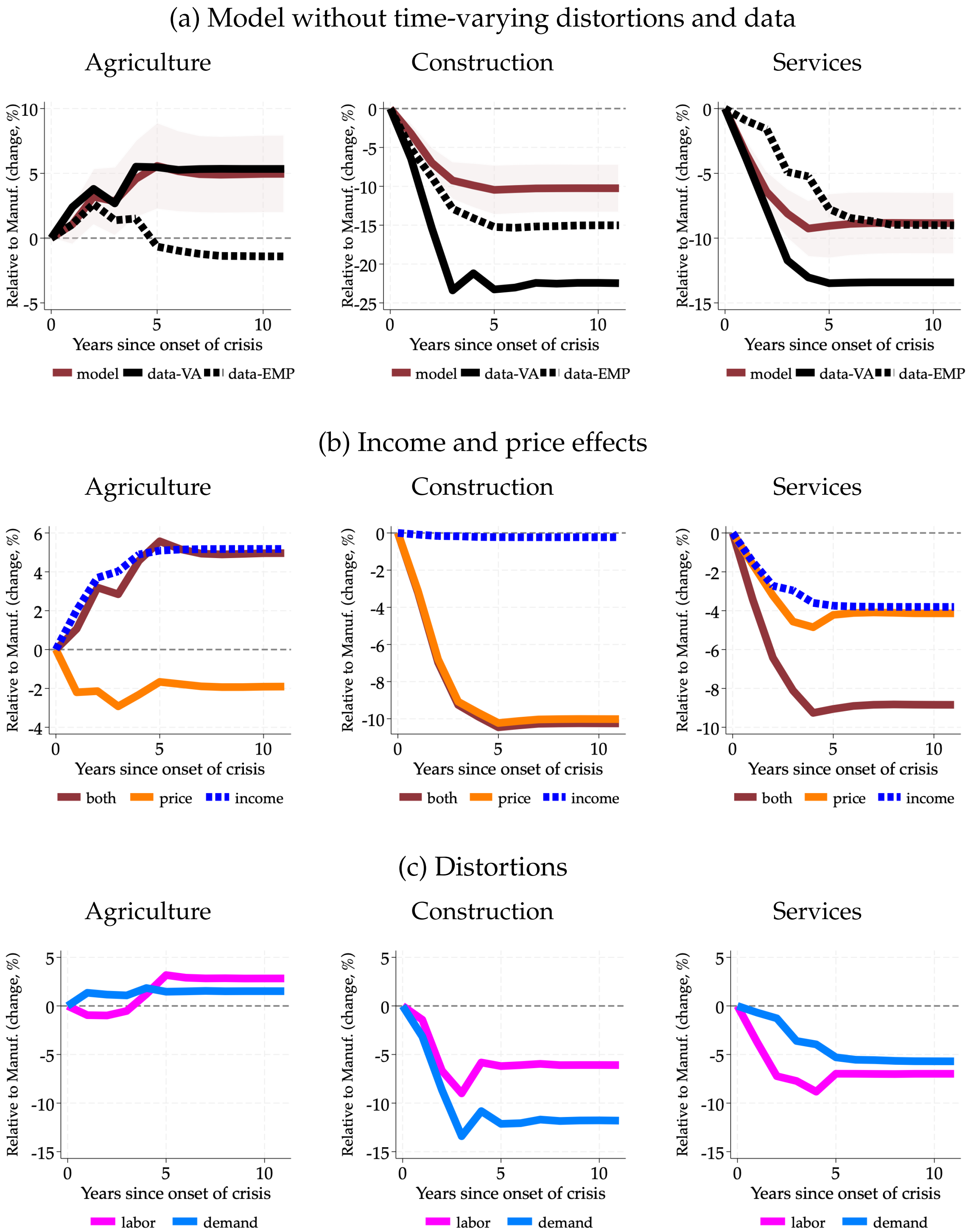


(c) Distortions



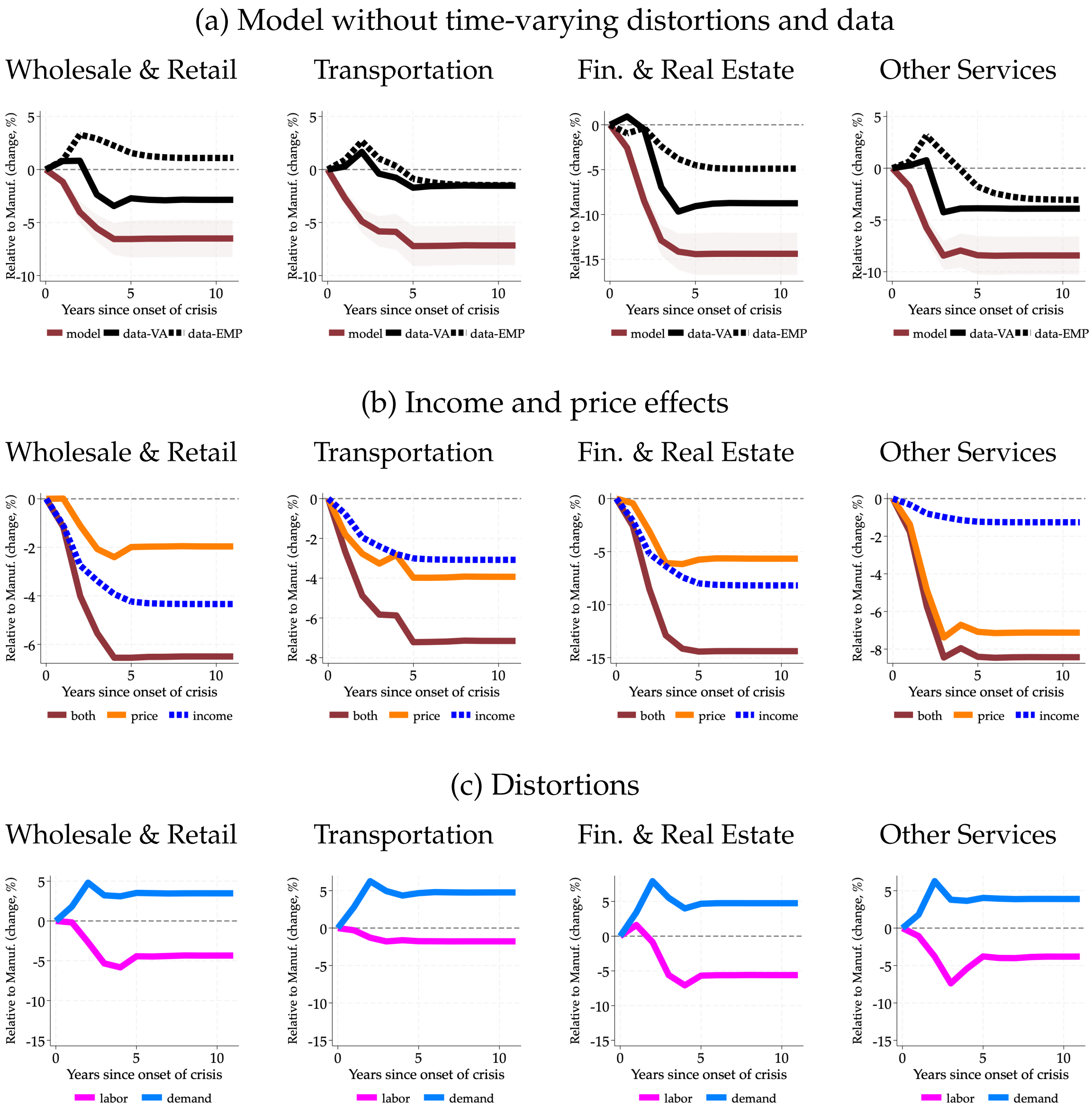
Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of sectoral reallocation and wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.20: Sectoral Reallocation during Crisis: Sovereign Debt Crisis



Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of sectoral reallocation and wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

Figure A.21: Sectoral Reallocation during Crisis: Within Services



Notes: All variables are relative to the manufacturing sector. The figures shows the crisis dynamics of sectoral reallocation and wedges. We fix $H = J = 4$ for our baseline estimates. Further details regarding the data and model are in the text.
Data sources: crisis dates and sectoral data sources are described in Section 2.1.

B Model Appendix

B.1 Production Linkages

In this section, we extend the model in Section 4 to allow for production linkages across sectors. We assume that gross output is produced with technology

$$Y_{it} = A_{it} K_{it}^{\alpha_i} L_{it}^{\nu_i} X_{it}^{1-\nu_i-\alpha_i},$$

where X_{it} is the intermediate input aggregator, which we assume to be Cobb-Douglas $X_{it} = \prod_{s \in \mathcal{I}} X_{sit}^{\gamma_{si}}$ with γ_{si} is the elasticity of sector s to sector i intermediate input aggregator and X_{sit} is the amount of good s used by firms in sector i.

$$\pi_{it} = p_{it} Y_{it} - (1 + \tau_{it}^{w}) w_t L_{it} - \left(1 + \tau_{it}^{k}\right) R_t K_{it} - p_{it}^{x} X_{it},$$

then the price aggregator $p_{it}^{x} = \prod_{s=1}^{N} p_{st}^{\gamma_{si}}$. Using the optimal conditions we can find the price of good i as

$$p_{it} = \chi\left(A_{it}, \tau_{it}^{w}, \tau_{it}^{k}; w_t, R_t, \alpha_i, \nu_i\right) \left(p_{it}^{x}\right)^{1-\nu_i-\alpha_i},$$

where $\chi\left(A_{it}, \tau_{it}^{w}, \tau_{it}^{k}; w_t, R_t, \alpha_i, \nu_i\right) = \left[\frac{\left(1+\tau_{it}^{w}\right)^{\nu_i} w_t^{\nu_i}}{\left(1+\tau_{it}^{k}\right)^{1-\alpha_i} R_t^{1-\alpha_i}}\right] \frac{\left(1+\tau_{it}^{k}\right) R_t}{A_{it} \alpha_i^{\alpha_i} (\nu_i)^{\nu_i} (1-\nu_i-\alpha_i)^{1-\nu_i-\alpha_i}}$. Using the definition of the intermediate input price aggregator and taking logs

$$\Delta \ln p_{it} = \Delta \ln \chi_{it} + \sum_{s=1}^{N} \left(1 - \nu_i - \alpha_i\right) \gamma_{si} \Delta \ln p_{st}.$$

Then stacking across sectors we can write

$$\begin{aligned} \Delta \ln \mathbf{p}_t &= \Delta \ln \chi_t + \Psi \Delta \ln \mathbf{p}_t \\ \Delta \ln \mathbf{p}_t &= \mathcal{H} \Delta \ln \chi_t, \end{aligned}$$

where Ψ is the Leontief matrix and $\mathcal{H} = (I - \Psi)^{-1}$ its inverse such that row i column s element is $\left(1 - \nu_i - \alpha_i\right) \gamma_{si}$. Thus, relative prices across sectors will depend on the structure of the matrix Ψ.

Propagation. For $\Delta \ln \chi$ shock, the relative prices would change by

$$\Delta \ln \frac{p_{it}}{p_{jt}} = \underbrace{\mathcal{H}_{(i,i)} \Delta \ln \chi_{it} - \mathcal{H}_{(j,j)} \Delta \ln \chi_{jt}}_{\text{direct}} + \underbrace{\sum_{s \neq i \in \mathcal{I}} \mathcal{H}_{(i,s)} \Delta \ln \chi_{st} - \sum_{s \neq j \in \mathcal{I}} \mathcal{H}_{(j,s)} \Delta \ln \chi_{st}}_{\text{indirect}},$$

where $\mathcal{H}_{(i,j)}$ is the element (i, j) of the $\mathcal{H}$ matrix. For example, for a shock to the labor distortion, we know that $\Delta \ln \chi_{it} = \nu_i \Delta \ln \left(1 + \tau_{it}^{w}\right)$. Then, ceteris paribus, the dynamics of relative prices will depend, through the network, on the entire distribution of labor distortion changes, not just the relative changes between i and j, as in the baseline model.