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WHICH U.S. STATES SUFFERED A GREATER GREAT DEPRESSION AND WHY?

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ABSTRACT

Aggregate real U.S. GDP fell by roughly 26 percent between 1929 and 1932, yet the severity of the Great Depression varied dramatically across states: CPI-deflated income per capita declined by 15 percent in Maryland but by 48 percent in South Dakota. To analyze this heterogeneity, we digitize Slaughter's (1937) panel of state-by-sector production income for all 48 U.S. states and construct a novel set of sector- and state-specific deflators, allowing us to separate movements in physical quantities produced from the large relative price changes that occurred during the Great Depression. We then discipline a three-sector, 48-region dynamic spatial stochastic general equilibrium model and recover sequences of sector-state productivity shocks that exactly reproduce the observed sector-state quantity paths. The choice of deflators proves central, as correct deflation shifts the aggregate contraction away from agriculture and toward manufacturing while preserving idiosyncratic income variation across agricultural-dependent states. We further show that narratives based on common or even sector-specific shocks are inconsistent with the observed evolutions of state-level quantities and relative prices. Explaining the geography of the Great Depression therefore requires a high-dimensional sector-state shock structure.

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1 Introduction

In his 1995 *Journal of Money, Credit and Banking* lecture, Ben Bernanke famously remarked that "to understand the Great Depression is the Holy Grail of macroeconomics." He further argued that "comparative country analysis improves our ability to identify ... the forces responsible for the world depression" by exploiting cross-country variation (Bernanke, 1995). This paper applies that logic *within* the United States by studying the geographic and sectoral incidence of the Great Depression across U.S. states.

The Great Depression is typically summarized by national aggregates: U.S. real GDP fell by about 26 percent from 1929 to 1932. Yet national accounts conceal an equally important feature of the episode: the Great Depression also witnessed a diverse allocation of economic losses across locations and sectors. Using CPI-deflated state production income, peak-to-trough contractions ranged from roughly 15 percent to 48 percent across states, a dispersion that vastly exceeds the cross-country variation over the same period.[1] This paper asks: Why did the Great Depression hit some U.S. states so much harder than others, and how did production specialization across states and sectors shape these distributional impacts?

Answering these questions is not merely descriptive. First, within-country heterogeneity helps quantify distributional consequences under incomplete risk sharing: workers' exposure depends on where they live and in which sector they work. The implications of this exposure depends on the geographic distribution of shocks and the resulting terms-of-trade movements that shape the cross-sectional patterns of aggregate downturns. Second, many U.S. states in the interwar period were economically large, some comparable in size to major countries. Thus, state-to-state trade and production specialization are quantitatively meaningful first-order propagation channels rather than trivial second-order model features.

A central obstacle to progress in understanding cyclical changes in income

[1] See also Garrett and Wheelock (2006) and Heim (1998) for empirical evidence documenting substantial heterogeneity in the incidence of the Great Depression across U.S. states.

distribution, is measurement. Interwar state accounts are primarily available as nominal income by sector; constructing real sectoral quantities requires an appropriate deflator. The standard practice of deflating nominal sectoral income with a common deflator, such as the CPI, conflates changes in relative prices with changes in physical output. This matters acutely in traded sectors where terms of trade move differently across goods and regions. In our data, agriculture provides a stark example: in 1931 agricultural production quantities rise even as agricultural income falls, implying that the early agricultural "collapse" is predominantly a deterioration in the agricultural terms of trade rather than a collapse in physical production. Measuring quantities of production as CPI-deflated production values, mechanically loads relative-price movements into measured "output," distorting both sectoral accounting and inference about the true underlying shocks.

We address these issues with two data contributions and one quantitative modeling contribution. First, we digitize and harmonize state-level income by sector for 48 contiguous states from Slaughter (1937) and organize the data into a three-sector structure: agriculture, manufacturing, and services. Second, we construct sector- and state-specific deflators for agriculture and manufacturing using historical microdata, which allows us to separate value movements from quantity movements at the sector-state level. This has not been done before. These deflators reveal that traded-sector dynamics differ sharply: during the deflationary contraction of the Great Depression, nominal agricultural income changes are dominated by collapsing commodity prices, whereas manufacturing prices and quantities move downward together in the contraction in a pattern consistent with the durable-goods propagation mechanism. This price-quantity separation is essential both for interpreting sectoral contributions to the Great Depression, and for mapping the data into a model expressed in real quantities.

Third, we develop a three-sector, 48-region dynamic stochastic general equilibrium model in which each state produces differentiated traded varieties of agriculture (non-durable) and manufacturing (durable, used for both consumption and investment), as well as a non-traded service. The model features production specialization across states and incomplete markets via trade in a non-contingent bond. To simulate the Great Depression, we recover sequences of sector-state productivity innovations that exactly reproduce the observed sector-state quantity paths.[2] Because the model abstracts from several important frictions and features, such as trade frictions, price rigidities, monetary policy, and financial constraints, the recovered shocks should be interpreted broadly as model-consistent efficiency wedges rather than literal measures of technological productivity. This allows us to exploit the rich cross-sectional variation in the Slaughter data, despite its short time dimension, to study equilibrium outcomes (relative prices, propagation, labor, and consumption) that are central for understanding the model mechanisms.

To illustrate the significance of price measurement, we run two parallel measurement regimes. In the *Baseline*, targets are sector-state quantities constructed by deflating nominal sector-state income using our sector- and state-specific deflators. In the *Alternative*, we follow common practice by deflating all sector-state nominal incomes by a common deflator (the CPI). This research design isolates the effect of mismeasurement from the effect of equilibrium structure.

Our main results are threefold. First, correct deflation changes the sectoral narrative of the Great Depression across states. Under sector-state deflation, manufacturing contributes disproportionately to the aggregate contraction relative to its income share, consistent with the stock-flow amplification of durable goods and the narrative by Hall (2010), while agriculture contributes relatively little to the aggregate contraction and remains weak in agriculture-intensive states during the recovery due to the timing of Dust Bowl-era quantity losses.[3] Under the common-deflator *Alternative*, agriculture appears to account for a much larger share of both the contraction and the recovery, especially in agriculture-intensive states. This is an artifact of attributing the agricultural income collapse to the physical quantity of production instead of the relative price of agricultural output.

[2] King and Rebelo (1999) named these shocks *Crucini residuals*.
[3] See Sichko (2021).

Second, correct deflation materially improves the model's predictions for relative-price dynamics. Because our shock-recovery procedure targets quantities, cross-state relative-price movements serve as an avenue for external validation. When quantities are correctly constructed using our sector-state deflators, the model matches the cross-sectional pattern of changes in the agriculture-to-manufacturing relative price substantially better: the fitted slope linking model-implied to observed relative-price changes is positive in both contraction and recovery under the *Baseline*, but weak and even negative under the common-deflator *Alternative*.

Third, cross-state heterogeneity in the Great Depression requires genuinely high-dimensional shocks. Counterfactuals restricting innovations to only one aggregate TFP shock (as in, for example, Chari et al., 2007) or only three sector-specific shocks, generate essentially no across-state income dispersion. Moreover, the measurement regime changes the inferred sectoral shock mix dramatically: under sector-only shocks, the *Baseline* implies a modest agricultural contraction while the *Alternative* implies a counter-factually severe one, illustrating how mismeasurement loads relative-price movements into recovered agricultural productivity and hence quantities. Under the genuine high-dimensional sector-state innovation structure, dispersion is largest in agriculture and manufacturing, with agriculture emerging as the dominant source of income dispersion once quantities are correctly measured.

The remainder of the paper is organized as follows: Section 2 discusses the related literature; Section 3 documents the cross-state and cross-sector facts about the Great Depression and introduces the measurement distinction between values and quantities; Section 4 presents the multi-sector, multi-region dynamic stochastic general equilibrium model; Section 5 describes the calibration and shock-recovery procedure; Section 6 reports results and the measurement comparison; and Section 7 concludes.

2 Related Literature

The macroeconomic literature on the Great Depression is vast and has gone through several distinct waves of development. Early contributions emphasized monetary policy failures (Friedman and Schwartz, 1963), banking crises (Bernanke, 1983), the collapse in durable-goods demand following the stock market crash (Romer, 1990), and the beggar-thy-neighbor Smoot-Hawley tariffs (Meltzer, 1976). These studies highlighted aggregate shocks and nationwide policy failures. A second generation of quantitative research embedded these explanations within dynamic general equilibrium frameworks, often interpreting the Great Depression through productivity shocks and policy distortions such as monetary contraction and tariffs (e.g., Cole and Ohanian, 2000, 2002, 2004; Chari et al., 2002, 2007; Crucini and Kahn, 1996; Kehoe et al., 2007; Beaudry and Portier, 2002). This literature substantially advanced discipline and measurement, but it primarily focused on national aggregates and recovered total factor productivity wedges from data sources reliant on a very sparse set of aggregate deflators.

Recent work has increasingly exploited spatial and micro-level variation to study the interwar economy and the Great Depression. Using disaggregated archival data, these studies identify the productivity and welfare effects of Smoot-Hawley tariff shocks (Bond et al., 2013), the impact of currency devaluations on cross-country output (Bouscasse, 2022), the role of trade - particularly the collapse of exports - in deepening the Great Depression (Candia and Pedemonte, 2025), and the political economy underlying the formation of the Smoot-Hawley tariffs (Irwin and Soderbery, 2021). As a whole, this work demonstrates that sectoral exposure and geographic specialization shaped local responses to national and global disturbances.

Our work also relates to the broader literature on geography, specialization, and international business cycles. Models emphasizing durable-goods amplification via stock-flow interactions (e.g., Baxter, 1996; Hall, 2010) show how sectoral composition can magnify aggregate fluctuations. Open-economy general equilibrium frameworks highlight how terms-of-trade movements redistribute income across regions under incomplete markets (e.g., Engel and Wang, 2011; Backus et al., 1992). More recently, quantitative spatial equilibrium models in international trade emphasize how trade linkages and regional specialization shape cross-sectional responses to shocks (e.g., Eaton and Kortum, 2002; Caliendo and Parro, 2015; Allen and Arkolakis, 2014; Kleinman et al., 2023).

We embed these insights in a dynamic multi-region framework with asymmetric production structures and region-sector-specific shocks. Our results show that explaining the geographic incidence of the Great Depression requires genuinely high-dimensional sector-state innovations and careful separation of prices from quantities, contributing both to the macroeconomic history of the Great Depression and to the more general questions of spatial propagation in quantitative macroeconomics.

3 The Great Depression: Nations, U.S. States, and Sectors

The quantitative analysis we undertake to describe the Great Depression and the predictions of our model follows the business cycle narrative approach formalized by Burns and Mitchell (1946). That is, the unit of account is not the frequency of observation nor the second-moment properties of the data, but rather the ebb and flow of macroeconomic activity from peak to trough during the business cycle episode under study. This approach works particularly well in historical contexts in which the available panel data comprise a short time dimension (7 years), but a very large cross-sectional dimension (48 regions and 3 sectors).

The term "Great" has been applied in the context to only two U.S. business cycles, the first being the Great Depression of the interwar period and the second being the more recent Great Recession. Using NBER official business cycle dates, the Great Depression contraction lasted 14 quarters compared to 5 quarters for the Great Recession. The Great Depression peak-to-trough real GDP loss was -26.4% compared to -3.4% during the Great Recession.[4] Simply put, the Great Depression was a factor of 2.8 longer and a factor of 7.7

[4] These statistics as well as the more detailed analysis of Table A.1 in the Appendix deflate all components of GDP by the GDP deflator.

deeper.

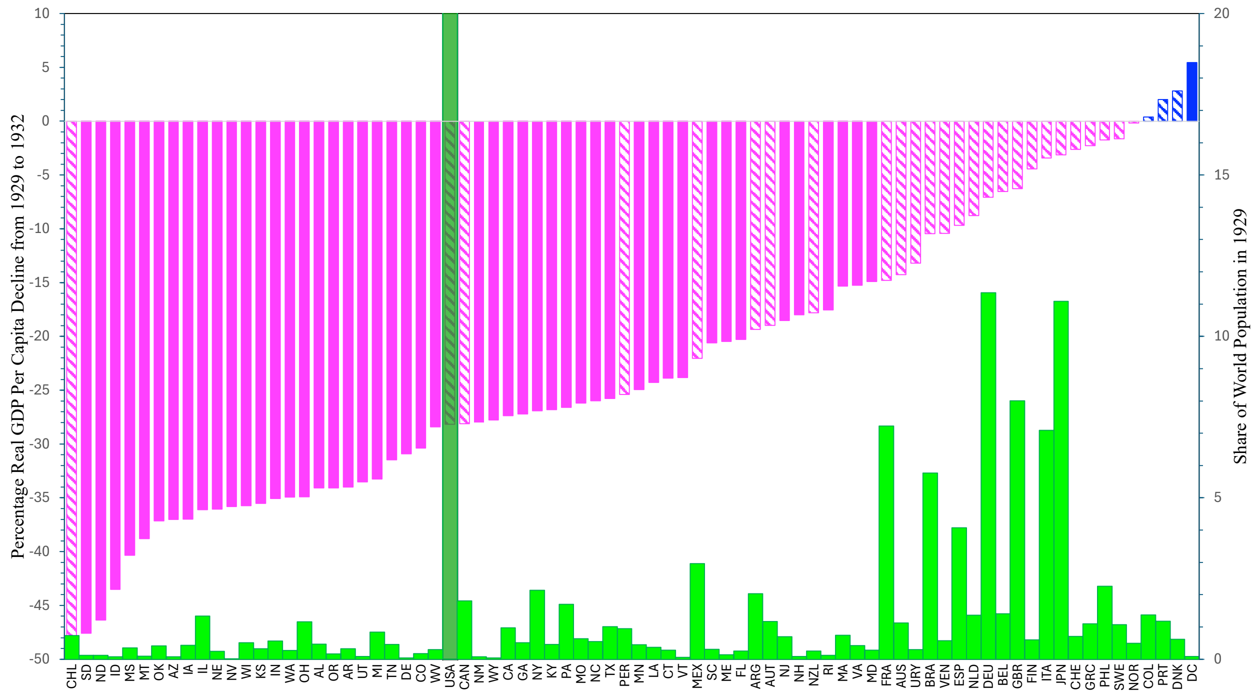
This section is organized into three parts. First, we document core facts on cross-state heterogeneity and motivate our focus on a three-sector structure with state-level variation. Second, we decompose nominal income changes into prices and quantities, highlighting the importance of distinguishing real physical output from value-based measures. While CPI-deflated series primarily reflect values, we construct sector- and state-specific price deflators to recover real quantities. Because our model simulations are expressed in terms of quantities, this distinction is essential for aligning the model with the data and for correctly identifying the sources of cross-state and cross-sector variation. Third, we present evidence on production specialization. We show that the U.S. exhibited stark specialization across the manufacturing and agriculture sectors and, crucially, they produced highly differentiated products within each of these sectors. This latter property contributes to terms of trade variation within sector, across states, which has not previously been systematically studied. These patterns play a central disciplining role for the model and are a key feature of the Great Depression's spatial propagation.

3.1 Nations versus States

Figure 1 compares the severity of the Great Depression across U.S. states and countries. Along the horizontal axis, we list 29 countries together with the 48 U.S. states and the District of Columbia. The figure reports two distinct measures. The right vertical axis, shown by green bars, displays each country's or state's share of world population. The United States accounts for roughly 20 percent of world population summarizing across all the 29 countries included in the accounting exercise, while other large economies such as Japan and Germany each constitute more than 10 percent. Notably, some U.S. states, such as New York and Pennsylvania, are comparable in population size to entire countries, underscoring the relevance of within-U.S. comparisons.

The left vertical axis reports peak-to-trough percentage changes in real GDP or real

Figure 1: **The Great Depression across U.S. States and Countries**



Note: This figure plots the percentage decline in real GDP per capita from 1929 to 1932 for 28 countries using data from the Maddison Project Database, and the percentage decline in CPI-deflated production income per capita for 48 U.S. states, the District of Columbia, and the U.S. aggregate using data from Slaughter (1937). Shares of world population in 1929 are on the right y-axis (in green), while GDP or production income declines in percentage terms are on the left y-axis (in pink and blue). U.S. states are in filed rectangles, while countries are in hollow rectangles with slashes. We distinguish the decline and rise in GDP or production income by color, pink for declines and blue for rises.

production income per capita from 1929 to 1932. Pink bars indicate contractions, while blue bars denote expansions. Solid bars correspond to U.S. states and dashed bars to countries. The figure orders states and countries by the magnitude of their peak-to-trough decline. Although the majority experienced contractions, three countries (Colombia, Portugal, and Denmark) and the District of Columbia exhibit positive growth over this period.

The aggregate U.S. experience is well known: aggregate real production income per capita fell by 28.2 percent from its 1929 peak to the 1932 trough. The international range of outcomes is wide, spanning a contraction of 48 percent in Chile to an expansion of 2.8 percent in Denmark. The central insight from Figure 1, however, is not the heterogeneity across countries but the even greater dispersion across U.S. states. State-level contractions ranged from 15 percent in Maryland to 48 percent in South Dakota. The median U.S. state experienced a decline of 28.4 percent, compared with just 7.9 percent for foreign countries. Indeed, 21 of the 28 foreign nations in the sample fared better than the least negatively affected U.S. state (Maryland). These stark differences motivate a closer examination of the geographic distribution of the Great Depression within the United States rather than across countries.

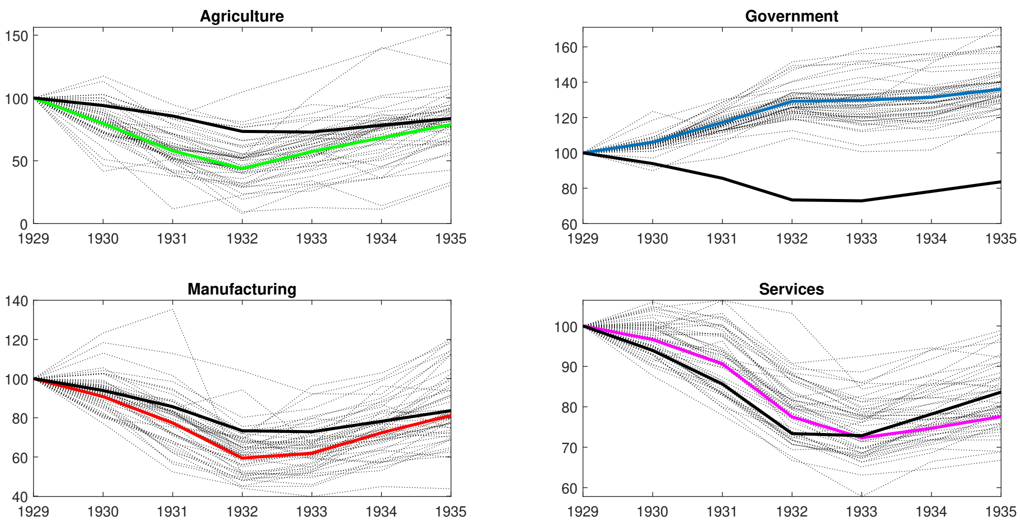
3.2 Sectoral and State-Level Income Dynamics

Unlike today, the National Income and Product Accounts are not available at the state level for the interwar period, precluding a decomposition of aggregate demand across states. However, Slaughter (1937) tabulated annual production income data by state for 12 sectors from 1929 to 1935, allowing for a supply-side (value-added) decomposition by sector and state.[5] We digitize these data and organize them to mirror the structure of our business cycle model. Specifically, we aggregate service, communications, construction, finance, trade, transportation, utilities, and miscellaneous activities into a single "service" sector. Agriculture and manufacturing correspond directly to the non-durable and durable sectors in the model and are already available in aggregated form in the Slaughter data.

Figure 2 plots sectoral income paths for each U.S. state alongside their national sectoral counterparts (the solid black line is aggregate U.S. income). From 1929 to 1932, total U.S. real income declines by 26.6 percent, closely matching the peak-to-trough contraction in GDP reported in the NIPA (see Table A.1 in the Appendix). Government income (blue line) is strongly countercyclical, rising by roughly 30 percent by the 1932 trough. In contrast, private-sector dynamics differ sharply across sectors. Services track aggregate income closely, while agriculture and manufacturing exhibit pronounced amplification. Real agricultural income collapses by 56.1 percent, followed by a 40.6 percent decline in manufacturing.

[5] We exclude mining and extraction, leaving 11 sectors in the panel.

Figure 2: **State and Aggregate Sector-Level Fluctuations Compared**



Note: The figure presents the movements of real income in the U.S. aggregate and by major sector and U.S. state. All series are CPI-deflated and normalized to 100 in 1929. Colored solid lines denote aggregate sectoral income, while the black solid line in each panel represents total U.S. income. Dotted gray lines show state-level sectoral income paths.

These sectoral patterns highlight an important limitation of aggregating services and non-durable goods on the income side, as is commonly done in aggregate demand decompositions. Services remain relatively stable throughout the contraction, whereas agricultural income collapses dramatically, reflecting a combination of large quantity declines and substantial relative price movements.

Turning to the cross-state dimension, the dotted gray lines in each panel reveal substantial heterogeneity in sectoral income dynamics across states. While state-level series broadly follow their aggregate U.S. counterparts, their amplitudes vary widely across states. In some states, sector-level declines are muted relative to the national average, while in others they are considerably amplified. This heterogeneity may reflect differences in production structure, population size, and exposure to sector-specific shocks.

A key feature of the state-level data is that states specializing in agriculture tend to be smaller in economic size, due to low population density. As a result, while agriculture accounts for only 9.8 percent of aggregate U.S. income, the simple average agricultural income share across states is substantially higher, at 15 percent. This distinction is consequential: agriculture not only exhibits higher average income volatility than other sectors, but also markedly greater heterogeneity across states. As shown in the variance decomposition presented in Table 1, these features make agriculture the largest contributor among these three sectors to cross-state income dispersion during the Great Depression.

The evidence from Figure 2 underscores two important facts that discipline our modeling approach in the next section. First, sectoral dynamics during the Great Depression differ sharply across agriculture, manufacturing, and services, with the former two traded sectors exhibiting far greater volatility. Second, these sectoral shocks translate into highly uneven state-level outcomes due to differences in specialization and economic size. Understanding the geography of the Great Depression therefore requires moving beyond aggregate decompositions toward a framework that jointly accounts for sectoral structure and spatial heterogeneity.

Furthermore, because nominal values are deflated by the CPI, relative price movements across sectors are incorrectly attributed to movements in real quantities. Agricultural prices fall much more sharply than manufacturing prices during this period, implying that CPI deflation overstates the physical decline in agriculture relative to manufacturing. Manufacturing nonetheless follows the amplified dynamics associated with durable goods demand, consistent with sharp contractions in both consumer durables and business investment. We return to this distinction in value and quantity movements in the latter part of this empirical section.

3.3 Sources of State-Level Income Variation

We now turn to a more quantitative analysis of state-level income variation across sectors. The contribution of a given sector to total state income volatility depends on three components: (i) the sector's time average share in state income, (ii) the volatility of sectoral income growth relative to aggregate state income, and (iii) the correlation

Table 1: **Contribution to State Income Variance**

	Agriculture	Manufacturing	Services	Government
Mean	0.386	0.292	0.351	-0.028
Median	0.362	0.272	0.343	-0.030
First quartile	0.152	0.118	0.268	-0.046
Third quartile	0.555	0.421	0.435	-0.016
Inter-q range	0.402	0.303	0.167	0.030

Note: The table reports the contribution of each sector to state income growth variance, defined as $\theta_{j,r}\beta_{j,r}$, where $\theta_{j,r}$ is the sector's time average income share and $\beta_{j,r}$ captures its relative volatility and comovement with aggregate state income. Entries summarize the cross-state distribution of these contributions.

between sectoral and aggregate state income growth. To formalize this decomposition, we begin by defining real state income as the geometric mean of CPI-deflated sectoral incomes:

$$Y_{r,t} = \prod_{j \in a,m,s,g} Y_{j,r,t}^{\theta_{j,r}}, \tag{1}$$

where $\theta_{j,r}$ denotes the average income share of sector j in state r over the sample period. Sector j can be agriculture (a), manufacturing (s), or government (g). Taking logs and first differences, $g_{r,t} = \Delta \ln Y_{r,t}$ and $g_{j,r,t} = \Delta \ln Y_{j,r,t}$, yields the following variance decomposition of state income growth:

$$1 = \sum_{j \in a,m,s,g} \underbrace{\theta_{j,r} \frac{\text{std}(g_{j,r,t})}{\text{std}(g_{r,t})} \text{corr}(g_{j,r,t}, g_{r,t})}_{\text{contribution of sector } j \text{ for state } r}, \tag{2}$$

where the term $\beta_{j,r} \equiv \frac{std(g_{j,s,t})}{std(g_{s,t})} corr(g_{j,s,t}, g_{s,t})$ captures the combined effects of relative volatility and comovement.

Table 1 reports the variance decomposition of state income growth, summarized across states.[6] On average, the service sector accounts for 35.1 percent of state income variance. This contribution is substantially smaller than its average income share of 52 percent, reflecting the relatively low volatility of service sector income. Consistent with

[6] The Appendix reports the underlying sectoral income shares and relative standard deviations that jointly determine these contributions.

this, the estimated β for services is well below unity (0.672), indicating that service sector income growth moves less than one-for-one with aggregate state income.

The government sector, which is also labor intensive, exhibits a negative contribution to income variability. This reflects a strong negative correlation between public sector income and aggregate state income, yielding an average contribution of -0.028 and a β of -0.274.[7] In a pure accounting sense, government activity did contribute to dampening income fluctuations in some regions, thought its overall role is quantitatively limited, as evidenced by its small average contribution to state income variance.[8]

In contrast, agriculture and manufacturing exhibit substantially larger contributions. Agriculture accounts for 38.6 percent of total state income variance, while manufacturing contributes 29.2 percent. Both are comparable in magnitude to services despite much smaller average income shares of 15 percent and 17.5 percent, respectively. This disproportionate contribution reflects large underlying β coefficients of 2.33 for agriculture and 1.60 for manufacturing, indicating systematic amplification relative to aggregate state income. In other words, income growth in these traded sectors responds more than one-for-one to aggregate fluctuations, leading them to play an outsized role in state-level income volatility.

Equally important, Table 1 shows that sectoral contributions to income volatility are highly heterogeneous across states, as reflected in the interquartile ranges. Agriculture and manufacturing exhibit substantial dispersion, with interquartile ranges of 0.40 and 0.30, respectively. By contrast, services are much more evenly distributed across states, with an interquartile range of 0.167, while government exhibits the least dispersion at 0.03. Given its low β, small income share, and minor contribution to volatility, we omit the government sector from the remainder of the analysis and focus on agriculture, manufacturing, and services. These sectors account for the dominant sources of cross-state income volatility during the Great Depression.

[7] An important exception is the District of Columbia, where government accounts for nearly 40 percent of income and exhibits a positive β of 0.735. In this case, government income cannot be countercyclical with itself.

[8] See, for example, Fishback et al. (2003), Romer (1992), among others.

3.4 Value versus Quantity: The Role of Sector-State-Specific Deflators

Thus far, we have documented substantial cross-state variation in income dynamics across sectors and shown that manufacturing and agriculture sectors account for a disproportionate share of this volatility. However, a key issue is how nominal sectoral incomes are deflated when making comparisons across sectors. Using a common aggregate deflator, such as the CPI, conflates changes in relative prices with changes in physical quantities. Because sector-specific prices can move very differently from the aggregate price level, a uniform deflator risks attributing relative price movements to quantity fluctuations.

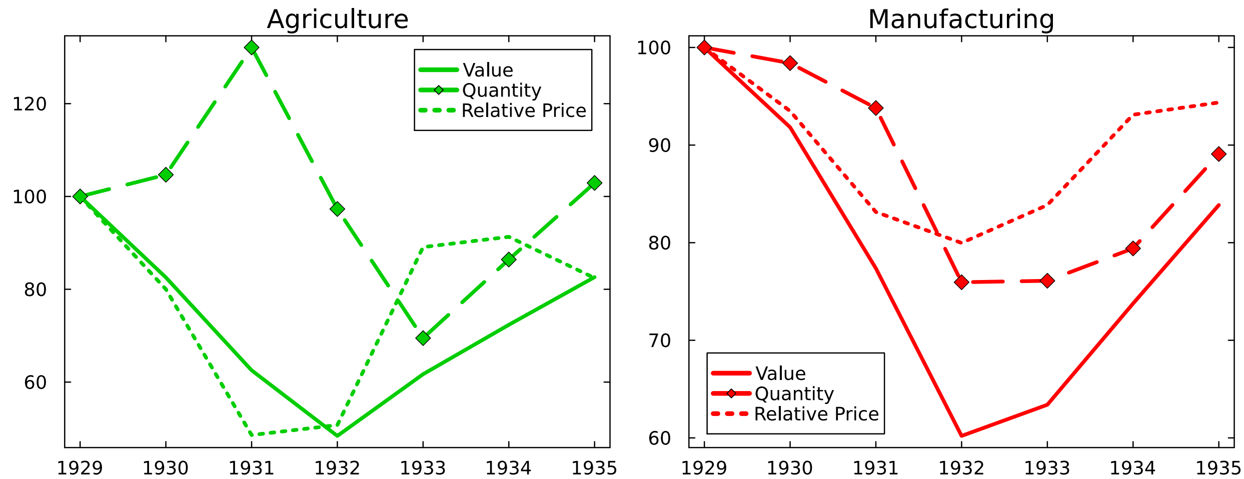
This issue is particularly relevant for agriculture. Results from the previous analysis indicate that the agriculture sector experienced the largest sectoral income decline during the Great Depression, even relative to manufacturing. Yet, the magnitude of the agricultural collapse implied by CPI-deflated income measures appears more consistent with popular narratives, such as John Steinbeck's *The Grapes of Wrath*, than with much of the academic literature on the Great Depression.[9]

To carefully address this issue, we construct state-level price indices for agriculture and manufacturing using micro data compiled from various historical archives. State-level agricultural price indices are constructed using crop-level data from the Agricultural Time Series-Cross Section Dataset (ATICS), originally compiled by Cooley et al. (1977). The dataset reports detailed information on prices and quantities for major crops across states, enabling us to disentangle movements in real quantities from changes in relative prices. State-level manufacturing price indices are constructed from a *newly* digitized panel of export unit values that we curate and assemble from the *Foreign Commerce and Navigation of the United States, 1927-1935*, which we combine with state-sector value-added data from the *Census of Manufactures, 1929*. These indices likewise allow us to separate quantity fluctuations from relative price movements. Additional details on the data sources and the construction of the price indices are

[9] For example, Wallis (1989) finds that employment in Southern states declined less than in Northern states. More recent work, such as Sichko (2025), shows that the severity of drought conditions did not peak until 1934.

provided in the Appendix.

Figure 3: **Agriculture and Manufacturing - Quantities and Relative Price**



Note: The figure plots time series of value, quantity, and relative price for U.S. agriculture and manufacturing from 1929 to 1935. All series are normalized to 100 in 1929.

Figure 3 plots three series for agriculture (left panel) and manufacturing (right panel): a population-weighted price index (normalized to 100 in 1929) as a proxy for the aggregate sectoral price level, the corresponding real quantity obtained by deflating nominal income by this price index, and the value series (price times quantity), which corresponds to the Slaughter income data used in the previous analysis. The dotted line in each panel represents the sectoral relative price. In both sectors, prices decline sharply during the contraction, but the price collapse is substantially larger in agriculture than in manufacturing.

Several features are worth emphasizing. Consider first agriculture. The value and quantity series diverge sharply in the early years of the contraction. In 1931, agricultural quantities rise even as the nominal value of this output falls. This initial decline in value is therefore driven almost entirely by relative price movements, i.e., by a deterioration in the agricultural terms of trade rather than by a collapse in physical production.[10] Prices begin to recover in 1933 and 1934, while the most severe quantity contraction coincides with the Dust Bowl period beginning in 1933.

[10]Madsen (2001) documents that sharp declines in agricultural prices played an important role in transmitting the Great Depression internationally.

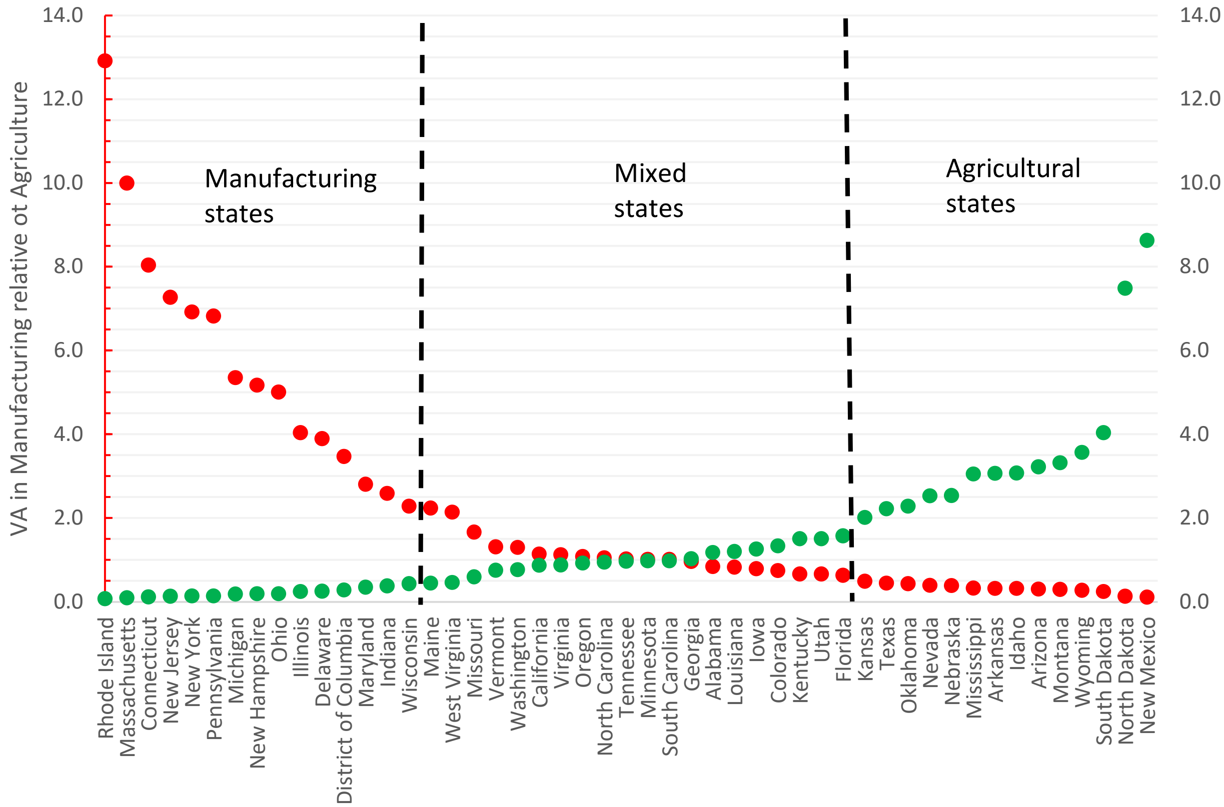
Manufacturing displays a markedly different pattern. In this sector, prices and quantities move together, reinforcing one another in terms of nominal manufacturing value added, rather than offsetting each other, as occurs in agriculture. Both manufacturing prices and quantities decline sharply around 1932, leading to a pronounced collapse in value added. While relative prices recover relatively quickly thereafter, quantities recover more slowly. This pattern is consistent with standard durable goods and capital adjustment mechanisms, in which declines in demand and investment generate persistent reductions in production even after prices begin to rebound.

3.5 Production Specialization across U.S. States

The preceding analysis establishes that cross-state income volatility is driven disproportionately by agriculture and manufacturing. These differences cannot be explained by sectoral income shares alone, but instead reflect systematic variation in how states specialize in production. We now examine the geography of production specialization, which provides a key link between sector-state specific shocks and the resulting dispersion in state-level outcomes. We further show that specialization becomes substantially more skewed when measured at the product level, a fact that is central, yet long neglected, in understanding terms-of-trade dynamics in the presence of intra-industry trade.

Figure 4 displays the distribution of sectoral specialization across states, measured by the ratio of manufacturing to agricultural value added (red dots) and its inverse (green dots), with states ordered along the horizontal axis based upon manufacturing specialization. The figure illustrates pronounced heterogeneity in production structure. At one extreme, Rhode Island produces more than twelve dollars of manufacturing value added for every dollar of agricultural value added. At the opposite extreme, New Mexico produces roughly nine dollars of agricultural value added for every dollar of manufacturing output.

Figure 4: **Distribution of Sectoral Income Across States in 1929**



Note: The figure presents ratio of value added in manufacturing to agriculture by state on the primary y-axis and the inverse ratio on the secondary y-axis.

In order to compare and contrast cyclical fluctuations based upon state-level specialization patterns, later in the analysis, the U.S. states are partitioned and aggregated into three groups: 14 agricultural states, 12 manufacturing states and 22 *mixed* or diversified states.[11] The District of Columbia is unique in the dominance of government services and is not included in the group aggregates for that reason.

Notice that North Dakota and New Mexico are extreme outliers in terms of agricultural specialization. There are 10 states with a ratio of manufacturing-to-agricultural income exceeding a factor of 4 and only 3 agricultural states with the inverse pattern.

[11]The 12 manufacturing states are: RI, MI, CT, NH, OH, MA, PA, DE, IN, NJ, WI, and IL. The 14 agricultural states are: KS, ID, TX, MS, AR, OK, NE, WY, MT, AZ, NV, SD, ND, and NM. The 22 *mixed* states are: ME, WV, MO, VT, WA, CA, VA, OR, NC, TN, SC, MN, GA, AL, LA, IO, CO, KY, UT, FL, NY, and MD. New York and Maryland are view as mixed despite skewing toward manufacturing because of the relatively large share of services in their income.

3.5.1 Product-level Specialization

Establishing facts about physical product-level specialization requires much more intensive archival work than we have accomplished to date. However, for the level of aggregation to the states, a few prominent products will help convey just how much more specialized states can be at the product level.

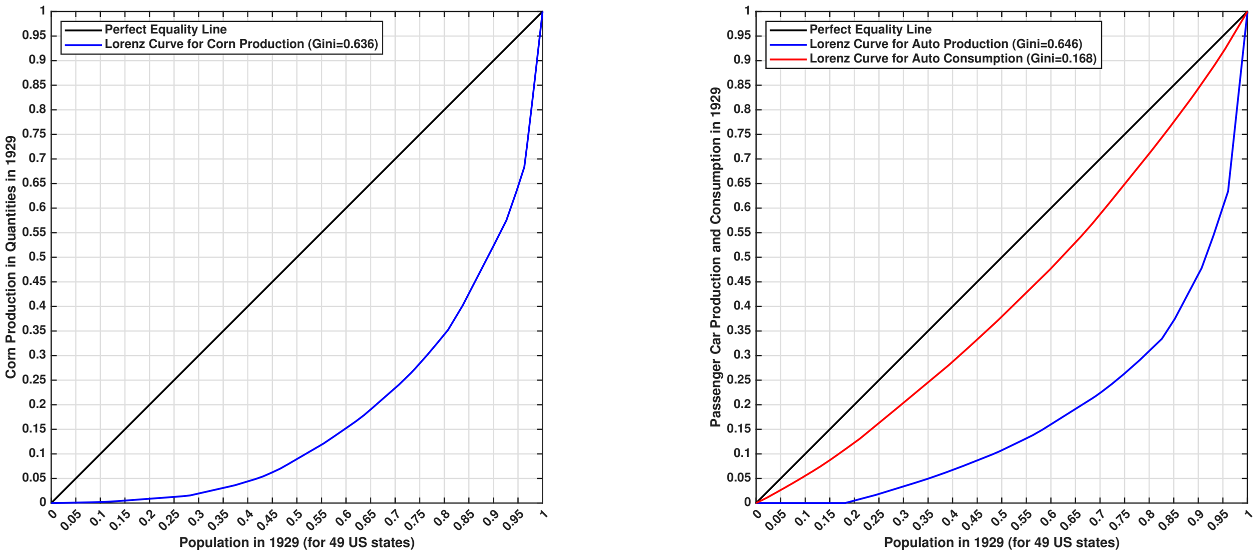
For the manufacturing sector, it is instructive to consider automobiles. At the turn of the 20th century the durable goods market looks very different from today. Consumer durables such as the automobile and household electric appliances were just starting to enter the marketplace. The automobile took the lead: the U.S. ranked first worldwide production and adoption of the automobile (Cheng et al., 2025), but 14th in terms of the share of the population in areas supplied with electricity (Hausman et al. (2011), Figure 1.6, page 28). Household appliances had to await the process of electrification which was particularly delayed in rural areas of the United States. In contrast, farmers adopted automobiles at much higher rates than individuals in urban areas.[12]

Figure 5 documents specialization for corn and automobiles, underscoring the extent of product-level geographic specialization. In each panel, the x-axis reports the cumulative share of the U.S. population (by state), and the y-axis the cumulative share of U.S. consumption or production, with states ordered by per capita production. The left panel, Figure 5a, presents the Lorenz curve for corn production across states. In agriculture, where relatively few crops account for the bulk of farm income, corn alone represents nearly 40 percent of total crop income in the ATICS database. Iowa produces 18 percent of total quantity of U.S. corn while accounting for only 2 percent of the population. The implied Gini coefficient for corn production is 0.636.

The right panel shows Lorenz curves for automobile consumption and production. Consumption is measured using state-level passenger automobile registrations, and production using Census of Manufacturing production data. Automobile consumption is close to geographically symmetric: by 1929, adoption was fairly uniform across states,

[12] According to *Facts and Figures of the Automobile Industry*, 1927 edition (page 15), approximately 64.5% of U.S. motor vehicle registrations were in towns and rural areas with populations under 25,000.

Figure 5: **Product-level Specialization**



(a) Corn (b) Automobiles

Note: The figure presents the cumulative distribution of corn production (left panel) and automobile production and consumption (right panel) using the of state population of the producing state as the x-axis.

yielding a consumption Gini coefficient of 0.168.[13] In contrast, automobile production was highly concentrated. The Lorenz curve is strongly bowed away from the 45-degree line, with a Gini coefficient of 0.646, reflecting pronounced geographic specialization. Michigan alone accounts for 37 percent of U.S. automobile production despite containing only 4 percent of the U.S. population.

By the accounting identity, the concentration of production implies substantial interstate trade, with exports from high per capita production to low per capita production states.[14] For reference, using the more aggregated Slaughter data, we continue to find the evidence of specialization in production: the service sector is the most equal (Gini of 0.217), while manufacturing and agriculture are more concentrated (Ginis of 0.339 and 0.294).

[13]Excluding major cities where density curtails automobile adoption would significantly reduce the across-state Gini coefficient for consumption.

[14]For the curious reader, U.S. automobile exports were consistently about 10% of domestic production. Imports were virtually nil.

4 The 3-Sector 48-Region DSGE Model

The model builds on the first generation of international real business cycle models. In one-sector versions of these models, steady-state productivity is equalized across countries, and economic size is determined by population. As a result, aggregate fluctuations reflect a population-weighted average of national business cycles.[15]

In our setting, the United States plays the role of the aggregate economy, analogous to the world economy in the international business cycle literature, since we treat the U.S. as closed. Individual U.S. states are modeled as small open economies whose relative economic sizes are determined by their population shares.

Each state (region) features three production sectors. Services produce a non-traded good consumed locally, while agriculture and manufacturing firms produce traded goods, a non-durable agricultural good and a durable manufactured good. Production in each sector-region pair is perfectly competitive. Following the Armington assumption (Armington, 1969), each state specializes in the production of a differentiated variety of each type of traded good, including agricultural consumption goods, consumer durables, and business investment goods, and consumers in all regions consume these varieties under a nested CES preference structure.

To capture cross-state heterogeneity and specialization, we allow states to differ in size and in the allocation of workers across sectors. Let N_{jr} denote the number of consumer-workers employed in sector $j \in a, m, s$ in region r. We work with population shares rather than levels and define $\pi_{jr} = N_{jr}/N$, where $N = \sum_j \sum_r N_{jr}$. This structure requires 144 sector-region representative agents, differentiated by their population weights π_{jr}, which map per capita variables into market-clearing aggregates.

The absence of a time subscript on the consumer-worker population share reflects our assumption of a fixed population share of agents within each sector-state pair. Put differently, laborers are treated as specific factors tied to a sector-location node. Allowing

[15]The role of relative economic size in international business cycle fluctuations was first modeled in Crucini (1991). Economic size in the paper was measured by total GDP to capture the effects of both population and income per capita on world market-clearing conditions.

for migration of labor across sectors and locations would enrich the model, but would not likely have a large quantitative impact on the economic geography of population in terms of equilibrium impacts on goods and factor-market prices. Moreover, common shocks across all sector-location pairs would not induce migration in the first place.

4.1 Households

Household preferences

In order to minimize our use of subscripts, we denote a representative agent residing in state r and working in sector j with the index i unless noted otherwise. Thus, each representative agent i maximizes its expected flow of utility from consumption, c_{it}, and leisure l_{it} (with $l_{it} = 1 - h_{it}$, where h_{it} denotes hours worked), according to the time-separable utility function,

$$U_{it} = \mathbb{E} \sum_{t=0}^{\infty} \beta^t u(c_{it}, h_{it}) = \mathbb{E} \sum_{t=0}^{\infty} \beta^t \left[\frac{(c_{it} - \chi h_{it}^{\theta} X_{it})^{1-\sigma} - 1}{1-\sigma} \right], \tag{3}$$

where $X_{it} = c_{it}^{\gamma} X_{it-1}^{1-\gamma}$. The utility function follows the functional form that is specified in Jaimovich and Rebelo (2009). The parameter on the labor supply, θ, is assumed to be greater than 1 and the parameter on risk aversion, σ, is assumed to be greater than 0. The parameter γ controls the strength of wealth effect on the labor supply. When $\gamma = 1$, the utility function corresponds to the case in King et al. (1988). When $\gamma = 0$, the utility function collapses to the one in Greenwood et al. (1988). All representative agents in the model have identical preferences no matter their sector or region of employment.

Consumption aggregation

Households consume non-traded services and traded goods. Preferences are nested CES. At the top level, households choose between services and the traded composite. At the second level, traded consumption is allocated between agricultural and manufactured goods. At the lowest level, agricultural and manufacturing goods are CES aggregates of region-specific varieties, following the standard Armington assumption.

Aggregate consumption of household i is given by

$$c_i = \left[\omega^{\frac{1}{\eta}} (c_i^s)^{\frac{\eta-1}{\eta}} + (1-\omega)^{\frac{1}{\eta}} (c_i^T)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{4}$$

where c_i^s denotes service consumption and c_i^T denotes consumption of the traded composite. The elasticity of substitution between services and tradables is η. Traded consumption is itself a CES aggregate of agricultural (non-durable) consumption c_i^a and manufactured (durable) consumption d_i,

$$c_i^T = \left[\psi^{\frac{1}{\varepsilon}} (c_i^a)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\psi)^{\frac{1}{\varepsilon}} d_i^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{5}$$

where ε governs the elasticity of substitution between agricultural (non-durable) and manufactured (durable) goods. The parameters ω and ψ, together with the elasticity parameters, determine steady-state expenditure shares.

Agricultural and manufacturing goods are CES aggregates of region-specific varieties. Let P_l^a and P_l^m denote the prices of agricultural and manufacturing varieties produced in region l. Conditional on aggregate consumption, household demand for varieties is

$$c_{il}^a = a_l \left(\frac{P_l^a}{P^a}\right)^{-\varepsilon_a} c_i^a, \qquad c_{il}^m = b_l \left(\frac{P_l^m}{P^m}\right)^{-\varepsilon_m} c_i^m, \qquad l = 1, \ldots, R, \tag{6}$$

where ε_a and ε_m are elasticities of substitution across agricultural and manufacturing varieties, respectively, and P^a and P^m are the corresponding aggregate price indices.

Price indices

Under frictionless trade, aggregate prices for agricultural and manufacturing goods are common across regions and are defined by the standard CES price indices

$$P^a = \left(\sum_{l=1}^{R} a_l (P_l^a)^{1-\varepsilon_a}\right)^{\frac{1}{1-\varepsilon_a}}, \qquad P^m = \left(\sum_{l=1}^{R} b_l (P_l^m)^{1-\varepsilon_m}\right)^{\frac{1}{1-\varepsilon_m}}. \tag{7}$$

The price index for traded consumption is then given by

$$P^T = \left[\psi (P^a)^{1-\varepsilon} + (1-\psi)(P^m)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}. \tag{8}$$

Finally, the consumer price index faced by households in region r is

$$P_r = \left[\omega(P_r^s)^{1-\eta} + (1-\omega)(P^T)^{1-\eta}\right]^{\frac{1}{1-\eta}}, \tag{9}$$

where P_r^s denotes the local price of non-traded services. Because services are non-traded, the CPI is region-specific, while prices of traded goods are common across regions.

Budget constraint and stocks

We follow early developments in the international business cycle literature in that population defines region size and agents are immobile across regions while capital is mobile (through trade in durables). Agents trade one-period non-contingent bonds, denoted by b_{it}.[16]

Thus, a representative agent i's budget constraint is given by

$$(\tfrac{1}{1+r_t^*})b_{it+1} - b_{it} = w_{it}h_{it} + u_{rt}^j k_{rt}^j - (P_t^m iv_{it} + P_{rt}^s c_{it}^s + P_t^a c_{it}^a + P_t^m c_{it}^m) - \Xi_{i,t}. \tag{10}$$

where $\Xi_{i,t} \equiv (\frac{1}{1+r_t^*})\frac{\phi_b}{2}(b_{it+1} - \bar{b}_i)^2$ is a small financial friction, and r_t^* is the U.S. interest rates on bonds. The wage rate, w_{it} and the rental rate of physical capital, u_{it}, are both sector-location specific (i.e., indexed by i). The former is such because of the immobility of labor and the latter due to the adjustment costs of physical capital in each sector-location. Finally, iv_{it}, is the amount of physical business investment at time t, by the individual in a particularly sector-region operating her firm.

Households in each sector own stocks of consumer durables, each one purchased from a different state (including the home state) and they also own a stock of sector-specific capital to operate their production process. The accumulation of durables and sector-specific capital is subject to quadratic adjustment costs, governed by the two parameters ϕ_m and ϕ_k. The law of motion of each representative agent's consumer durable stock is

$$c_{it}^m = d_{it+1} - (1-\delta_m)d_{it} + \frac{\phi_m}{2}(\frac{d_{it+1}}{d_{it}} - 1)^2 d_{it}, \tag{11}$$

where δ_m is the depreciation rate for durable goods. The law of motions of each

[16]For early developments in the literature on the consequences of incomplete markets across geographies with immobile labor, see Baxter and Crucini (1995) and Kehoe and Perri (2002).

representative agent's production capital stock is

$$iv_{it} = k_{it+1} - (1-\delta_k)k_{it} + \frac{\phi_k}{2}(\frac{k_{it+1}}{k_{it}} - 1)^2 k_{it}, \tag{12}$$

where δ_k is the depreciation rate for capital. As with consumer durables, business investments goods, iv^a, iv^m, and iv^s, are composites of intermediate investment goods, which are sourced from different regions including the home state. Intermediate investment demands are given by

$$iv_l^a = b_l \left(\frac{P_l^m}{P^m}\right)^{-\varepsilon_m} iv^a, \quad iv_l^m = b_l \left(\frac{P_l^m}{P^m}\right)^{-\varepsilon_m} iv^m, \quad iv_l^s = b_l \left(\frac{P_l^m}{P^m}\right)^{-\varepsilon_m} iv^s, \qquad l = 1, ..., R, \tag{13}$$

4.2 Firms

Each sector-region representative consumer-worker operates a representative firm that behaves in a perfectly competitive manner. Each sector of the economy requires capital and labor as factors of production.[17] Letting y_{it} be the output produced by sector j in region r, at time t, we have

$$y_{it} = z_{it}F(k_{it}, h_{it}) = z_{it}k_{it}^{\alpha}h_{it}^{1-\alpha} \qquad i = jr, \quad j = a, m, s, \quad r = 1, ..., R, \tag{14}$$

where α is the capital share which is assumed to be equal across regions and sectors, and z_{it} is the productivity level of sector j in region r at time t.

Productivity in each sector-location pair follows an AR(1) process

$$z_{it+1} = \rho z_{it} + \epsilon_{it+1}, \qquad i = jr, \quad j = a, m, s, \quad r = 1, ..., R, \tag{15}$$

Notice that a general vector-autogression for the productivity shock process would require a 147 by 147 matrix of estimated parameters, which is both statistically infeasible given the sample size of our underlying data and likely significantly over-parameterized for this period of history. As such, the productivity processes are assumed to be

[17] The reader is reminded that the variable, l_{it}, represents the fraction of hours devoted to leisure by the representative agent i. The fraction of hours devoted to work, by this agent is thus, $h_{it} = 1 - l_{it}$. This adjustment represents the intensive margin of adjustment in the labor market.

univariate processes with a common persistence parameter across sector-location pairs, but an unrestricted variance-covariance structure of innovations, denoted by V_ϵ.

The twin assumptions of common diagonal persistence in the vector-autoregressive structure and unrestricted variance-covariance structure of the innovations are powerful in the context of first-order approximate solutions. The reason is that the decision rules arising from these solution methods do not depend on the structure of the variance covariance matrix of the innovations, but do change with alterations to the persistence structure of the shocks across sector-location pairs or in terms of dynamic spillovers across them.

4.3 Market Clearing Conditions

At the regional level, the resource constraints for services are

$$\sum_{j=\{s,d,n\}} \pi_{jr} c^s_{jrt} = \pi_{sr} y^s_{jrt}, \qquad r = 1, ..., R. \tag{16}$$

At the national level, markets clear for agricultural, manufacturing, and bonds.

$$\sum_{l=1}^{R} \sum_{j=\{s,a,m\}} \pi_{jl} (c^m_{jlrt} + iv_{jlrt}) = \pi_{mr} y^m_{rt}, \qquad r = 1, ..., R \tag{17}$$

$$\sum_{l=1}^{R} \sum_{j=\{s,a,m\}} \pi_{jl} c^a_{jlrt} = \pi_{ar} y^a_{rt}, \qquad r = 1, ..., R \tag{18}$$

$$\sum_{l=1}^{R} \sum_{j=\{s,a,m\}} \pi_{jl} b_{jlt} = 0. \tag{19}$$

5 Calibration and Simulation Methodology

5.1 Calibration

This subsection describes the calibration of the baseline model. Time is discrete. The economy is assumed to be in steady state through 1929, after which sector-state productivity shocks drive the observed dynamics. Unless stated otherwise, the model frequency matches the annual frequency of the data.

To highlight the general equilibrium interaction of sectoral shocks, production specialization, and intrinsic sectoral dynamics, the model imposes parametric symmetry across regions and sectors in all dimensions except two. First, economic gravity in sector-state labor markets is governed by population shares, denoted by π_{jr}. Second, sector-state productivity processes are disciplined so that model simulations exactly reproduce the observed paths of real output in each sector-state pair over the sample period.

Parameters and steady-state objects are grouped into three categories: (i) parameters calibrated using interwar data, (ii) parameters taken from the broader macroeconomic literature, and (iii) population and sectoral employment shares that discipline regional economic size and production specialization. Table 2 summarizes the full set of baseline parameter values.

Interwar-calibrated parameters. We externally calibrate parameters specific to the interwar period whenever possible. Following Crucini and Kahn (1996), the real interest rate is set to $r^* = 0.05$ and the depreciation rate of physical capital to $\delta_k = 0.10$. The depreciation rate of durable goods is higher and set to $\delta_m = 0.20$, which is consistent with Cheng et al. (2025) for the case of automobiles during the early 20th century. The capital share of income is set to $\alpha = 0.38$, consistent with historical estimates.[18] Preference weights in the CES aggregators, ω and ψ, are chosen to match observed national income shares of services (60.0%), agriculture (12.8%), and manufacturing-related durable goods and investment (27.2%) for this historical period. This yields $\omega = 0.78$ and $\psi = 0.86$. Elasticities across product varieties within agriculture and manufacturing are set to 5 and 7, respectively. These values are across-product medians of interwar Armington trade elasticities estimated by Crucini et al. (2026). There are 372 agricultural products and 181 manufacturing products in their interwar panel dataset.

Parameters from the literature. Panel B of Table 2 reports parameters that are difficult to

[18] See, for example, Kendrick (1961).

Table 2: **Parameters Used in the Baseline Model**

Symbol	Value	Description
Panel A: Parameters Specific to the Interwar Period		
r^*	0.05	Real interest rate
δ_k	0.1	Physical capital depreciation rate
δ_m	0.2	Manufactured (durable) goods depreciation rate
α	0.38	Capital income share
ω	0.78	CES preference parameter on services
ψ	0.86	CES preference parameter on agricultural
ε_a	5	Substitution elasticity across agricultural products
ε_m	7	Sustitution elasticity across manufacturing products
ρ	0.42	Median persistence of productivity shocks
Panel B: Parameters Not Specific to the Interwar Period		
σ	2	Risk aversion
γ	1	Wealth effect parameter
χ	1.73	Disutility of labor
θ	1.4	Labor supply parameter
ϕ_b	1e-5	Bond adjustment cost
ϕ_k	0.67	Capital adjustment cost
ϕ_m	0.33	Manufactured (durable) adjustment cost
η	0.73	Traded and service substitution elasticity
ε	1.1	Manufacturing and agricultural substitution elasticity

discipline directly using interwar data. We set risk aversion to $\sigma = 2$, a standard value in the business cycle literature. The wealth effect parameter γ is set to 1, corresponding to King et al. (1988). The labor supply elasticity parameter θ is set to 1.4 following Jaimovich and Rebelo (2009), and the disutility of labor parameter χ is chosen to imply a steady-state labor supply of one third.[19]

We calibrate three adjustment costs. The bond adjustment cost, ϕ_b, is set to a negligible value. The capital and durable adjustment costs follow Baxter and Crucini (1995), targeting an elasticity of the investment-capital ratio (and durable stock-flow ratio) with its respective shadow value of the stock variable of 15. This target implies values of 0.67 for capital and 0.33 for durables, respectively.

[19]The one-third calibration is consistent with standard RBC models of the Great Depression, such as Cole and Ohanian (2000), and with historical evidence on hours worked in the interwar U.S. economy documented by Kendrick (1961).

There are four elasticities of substitution governing consumption decisions. The elasticity between services and tradables, η, is set to 0.73 following Corsetti et al. (2008). The elasticity between agricultural and manufacturing goods, ε, is set to 1.1 following Engel and Wang (2011).

Economic gravity and steady-state discipline. Regional heterogeneity arises from differences in population size and production specialization. State population shares π_r are fixed using data in 1929. Sectoral employment shares π_{jr} are chosen to equalize relative prices in the steady state, ensuring no incentives for migration at the calibrated allocation. Variety preference weights are set proportional to employment shares, $a_l = \pi_{al}$ and $b_l = \pi_{ml}$, which helps keep steady-state prices comparable across regions.

5.2 Simulation Methodology

The objective of the simulation methodology is to document and explain the pronounced heterogeneity of the Great Depression across sectors and states. To this end, we simulate the equilibrium paths of sector-state output and discipline the model so that its predictions match the historical income paths observed in the Slaughter data.

Specifically, conditional on the calibrated model and the assumed persistence parameter, we recover sequences of sector-state productivity innovations that reconcile the model's decision rules with the observed evolution of real output by sector and state. Following King and Rebelo (1999), we refer to these inferred productivity shocks as *Crucini residuals*. Unlike *Solow residuals*, which are constructed directly from production functions and measured inputs, *Crucini residuals* are defined as the productivity processes that, conditional on the full general equilibrium model, exactly reproduce observed real output paths.

An important advantage of this approach is that it delivers a perfect historical fit for sector-state income paths while avoiding potential measurement errors arising from misspecified production functions or mismeasured factor inputs. This allows us to exploit the rich cross-sectional variation in the Slaughter data despite its relatively short time dimension and to study how sector-state shocks propagate to welfare-relevant outcomes such as consumption and labor. However, because these paths are matched by construction, the model's goodness-of-fit for these quantities cannot be used as a basis for rejection. We therefore evaluate the model using an untargeted moment: cross-state movements in the agricultural-to-manufacturing relative price.

The model abstracts from monetary policy shocks via price rigidities, intermediation shocks via bank failures as well as tariff shocks and thus attributes all unexplained variation to productivity shocks. The recovered productivity shocks should be interpreted broadly as model-consistent efficiency wedges. These wedges summarize the combined effects of multiple underlying disturbances rather than purely technological shocks.[20]

Using this procedure, we can also discipline the persistence parameter, ρ. We begin with an initial guess for the persistence parameter, ρ_0. Conditional on this value, we employ the methodology outlined previously to recover the productivity paths that perfectly match the income data. Using this, we re-calculate the persistence of the productivity process and repeat the procedure until convergence.

This approach yields a distribution of persistence estimates across sector-state pairs. To avoid overstating regional heterogeneity driven by differences in persistence rather than shocks themselves, we use the median of these estimates as the baseline persistence parameter. The resulting value is $\rho = 0.42$, which corresponds to a quarterly persistence of approximately 0.81.[21] The mechanics of the shock recovery procedure are described in detail in the Appendix.

[20] Crucini and Kahn (2007), for example, demonstrate the mathematical equivalence of the production efficiency effects of tariffs on intermediate inputs and what would be measured as a Solow residual in the one-sector, two-country neoclassical model.

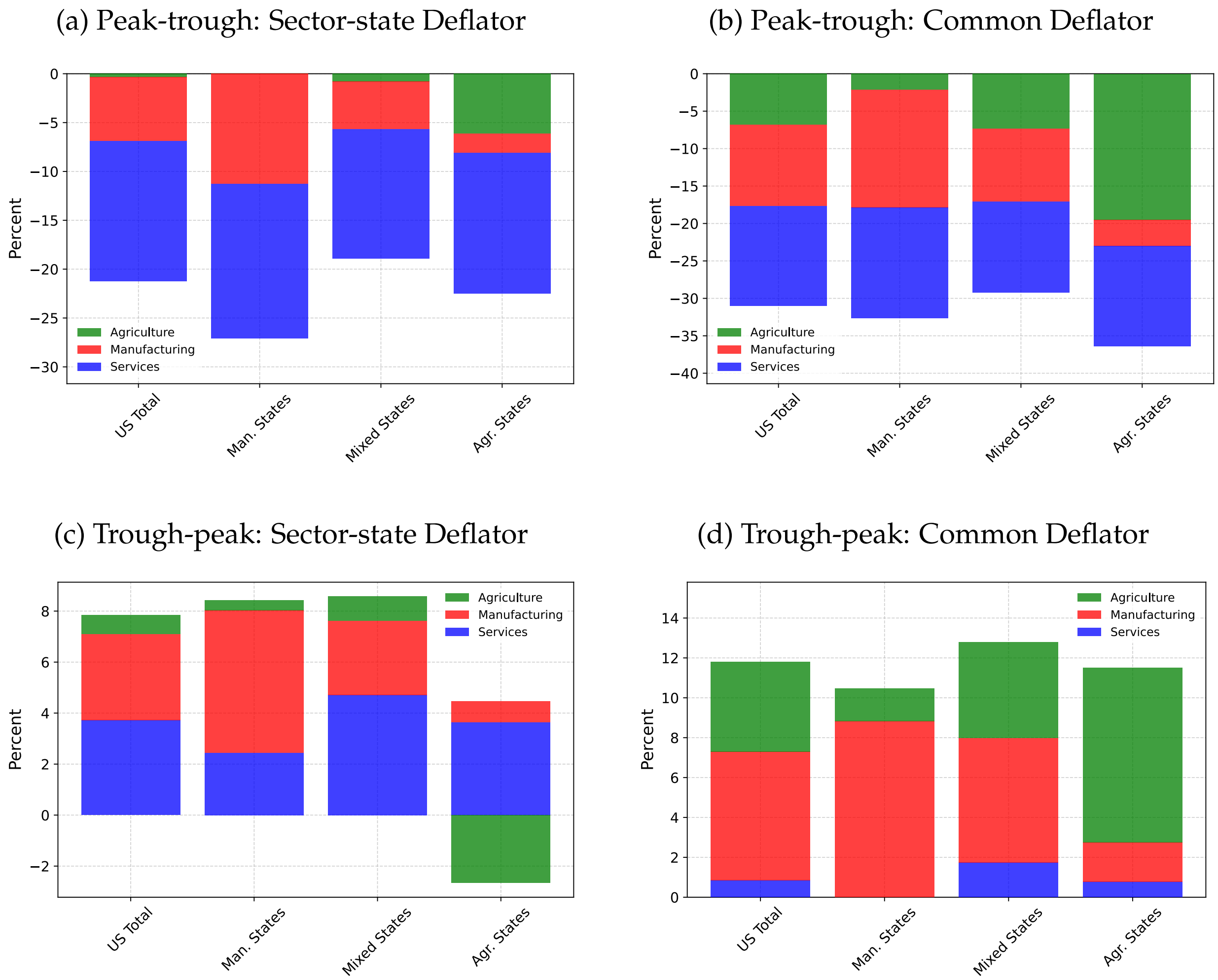
[21] Results are robust to alternative values within a reasonable range.

6 Cross-State Transmission of the Great Depression

This section quantifies the extent to which geography drives the Great Depression dynamics in the model. Building on the calibration and shock-recovery procedure in the previous section, we run the model under two measurement regimes. In the *Baseline*, the targeted sector-state "quantities" are constructed by deflating nominal sectoral income using sector- and state-specific deflators; in the *Alternative*, we follow the common practice of deflating nominal income using CPI or other common national deflators to obtain "quantities". In each regime we recover sector-state productivity innovations (*Crucini residuals*) that exactly reproduce the corresponding sector-state quantity paths, so differences in implied terms of trade, propagation, and incidence reflect the measurement regime rather than differences in fit. We organize the results around the Burns-Mitchell narrative by reporting peak-to-trough changes (1929-1932) and trough-to-peak changes (1932-1935), and we summarize cross-state patterns using manufacturing-intensive, agriculture-intensive, and diversified state groups when appropriate. We proceed in four steps: (i) sectoral accounting decompositions of aggregate and group outcomes, (ii) an untargeted validation moment based on cross-state movements in the agriculture-to-manufacturing relative price, (iii) model-implied general-equilibrium incidence to quantify deflator importance and (iv) exploring mechanisms that clarify how specialization and shock dimensionality generate dispersion across states.

Figure 6 reports a steady-state share-weighted decomposition of changes in real income into agriculture, manufacturing, and services for the U.S. aggregate and for three state groups (manufacturing-intensive, agriculture-intensive, and diversified). Figure 6a and Figure 6b correspond to the peak-to-trough contraction (1929-1932), and Figure 6c and Figure 6d correspond to the trough-to-peak recovery (1932-1935). The left column uses sector-state deflators (*Baseline*), while the right column uses a common CPI deflator across sectors and states (*Alternative*). Within each bar, the sectoral components sum to the total change in real income for the corresponding group. Red bars denote manufacturing, green bars agriculture, and blue bars services.

Figure 6: **Sectoral Contribution to GDP by State Groups**



Note: This figure reports steady-state share-weighted sectoral contributions to changes in real GDP for the U.S. aggregate and for three groups of states: manufacturing-intensive, agriculture-intensive, and diversified. Red bars denote manufacturing, green bars agriculture, and blue bars services. The top row shows peak-to-trough changes (1929-1932), and the bottom row shows trough-to-peak changes (1932-1935). The left column uses sector-state-specific deflators (*Baseline*), while the right column uses a common CPI deflator across sectors and states (*Alternative*). Within each bar, sectoral contributions sum to the total change in real GDP for the corresponding group.

Two features of the *Baseline* decomposition are especially notable. First, services account for a large fraction of the aggregate contraction, approximately 14 percentage points, reflecting their dominant income share in 1929 (about 60 percent). Second, manufacturing contributes disproportionately relative to its steady-state share. Although manufacturing accounts for roughly 27 percent of income, it explains about one third of total real output decline, consistent with durable-goods and capital adjustment mechanisms that amplify downturns in the traded durable sector. By contrast, agriculture contributes little to the aggregate contraction, and its quantitative importance is concentrated in agriculture-intensive states.[22]

The recovery patterns are equally informative. Under the *Baseline* deflation regime, manufacturing and services together account for most of the rebound in the U.S. aggregate and in manufacturing-intensive and diversified states, contributing roughly equally, while agriculture continues to play only a minimal role in the recovery. In agriculture-intensive states, however, the agricultural contribution remains negative even during the recovery phase. This pattern is consistent with the timing of Dust Bowl-related quantity losses, which intensify after the national trough and dampen subsequent income growth in agricultural regions.[23]

The *Alternative* (common-deflator) decomposition yields a qualitatively different narrative. In particular, agriculture appears to account for a much larger share of both the peak-to-trough contraction, approximately 7 percentage points, and the trough-to-peak recovery, about 5 percentage points. This is most stark in agriculture-intensive states, where agriculture accounts for nearly 20 percentage points during the contraction and roughly 9 percentage points during the recovery. This pattern is consistent with conflating large traded-sector relative-price movements with physical quantity movements when real output is estimated by deflating nominal national income by the national CPI-deflator.

Because sector-state outputs are matched by construction in both simulations, the decomposition in Figure 6 should be interpreted as an accounting exercise that maps measured sectoral quantities into aggregate and group-level outcomes. The next natural question, therefore, is whether the measurement discipline of sector-specific deflation improves the model's ability to match key variables that are not directly targeted. We focus in particular on relative prices, especially those between agriculture and

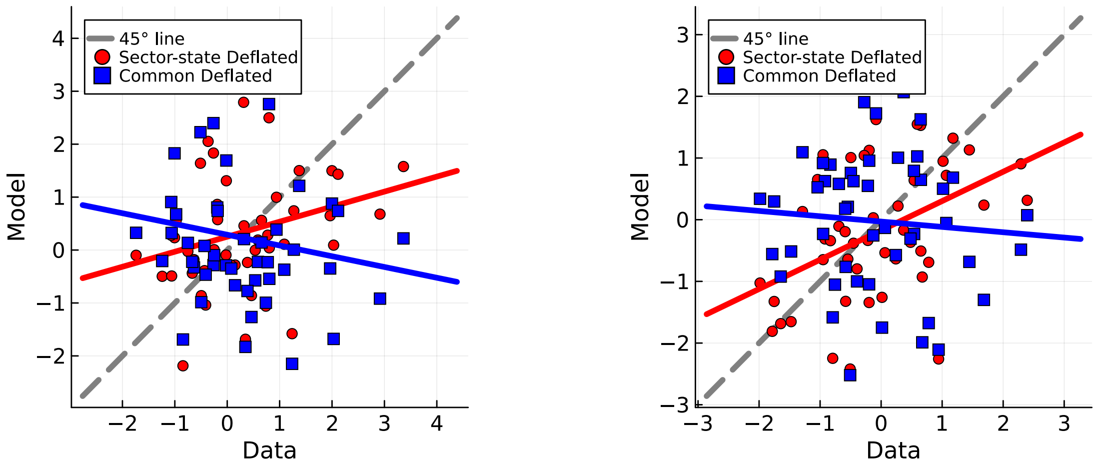
[22]Consistent with our results, Federico (2005) finds that agriculture was not a primary driver of the onset of the Great Depression.

[23]For further evidence on the economic costs of the Dust Bowl, see Hornbeck (2012).

Figure 7: **Relative Price Dynamics – Agricultural over Manufacturing, (P_r^a/P_r^m)**

(a) Peak-trough

(b) Trough-peak



Note: Each point represents a U.S. state. The horizontal axis reports observed changes in the agriculture-to-manufacturing relative price, P_r^a/P_r^m, while the vertical axis reports the corresponding model-implied changes. The left panel shows peak-to-trough movements (1929-1932), and the right panel shows trough-to-peak movements (1932-1935). All variables are standardized by subtracting the mean and dividing by the standard deviation to emphasize cross-state dispersion.

manufacturing, and turn to those next.

6.1 Relative Price Dynamics across States

We evaluate the model using cross-state changes in the agriculture-to-manufacturing relative price, P_r^a/P_r^m. This object is not directly targeted in the shock-recovery procedure: we discipline the model to match sector-state quantity paths, and the resulting equilibrium implies producer prices for each state variety. Relative prices therefore provide an external check on whether the *Baseline* measurement regime yields a more coherent mapping from observed quantities into implied terms of trade.

Figure 7 compares state-level changes in P_r^a/P_r^m in the data to the model-implied changes under the *Baseline* (sector-state deflators) and *Alternative* (common CPI deflator) simulations, separately for the contraction and recovery phases. Both axes are standardized (demeaned and divided by their standard deviation) to emphasize cross-state comovement rather than levels; accordingly, the fitted slope provides a transparent summary statistic for how well the model reproduces the cross-sectional pattern in relative-price changes.

The *Baseline* specification aligns substantially better with the data. In both the contraction and recovery, the *Baseline* implies positive cross-state comovement between model-implied and observed relative-price changes, moving the fitted relationship toward the 45-degree benchmark. By contrast, under the common-deflator *Alternative*, the fitted relationship is weak and of the wrong sign, consistent with treating relative-price movements as quantity movements in the underlying targets used to discipline the model. Quantitatively, the slope of the fitted relationship under the common-deflator case is -0.2 during the contraction and -0.08 during the recovery, whereas under the sector-state deflated Baseline, the corresponding slopes are 0.29 and 0.48, respectively.

Taken together, Figures 6 and 7 show that correct deflation matters in two complementary senses: it changes the sectoral accounting of the Great Depression across the U.S. states, and it materially improves the model's ability to reproduce the cross-state terms-of-trade movements that are central for distributional incidence of income variation. We therefore use the *Baseline* as our benchmark measurement regime going forward, while continuing to report the *Alternative* results to quantify how mismeasurement alters general-equilibrium propagation and welfare-relevant outcomes.

6.2 General Equilibrium Propagation, Labor, and Consumption

Having shown that the *Baseline* sector-state deflators better align the model with observed cross-state movements in the agriculture-manufacturing relative price, we now turn to the model-implied outcomes that are central for business cycle incidence and propagation mechanisms. These objects, general equilibrium propagation, labor, and consumption, are not targeted directly by the shock-recovery procedure, but are pinned down by the equilibrium mapping from recovered productivity innovations into wages, prices, and quantities.

To isolate the role of measurement, we use a common visualization across outcomes. For each sector j and state r, we plot the *Alternative* outcome (with common deflator) on the horizontal axis against the *Baseline* outcome (with sector-state deflator) on the vertical axis, separately for the peak-to-trough contraction and trough-to-peak recovery. If measurement is irrelevant, observations lie on the 45-degree line. Systematic departures from the 45-degree line capture level shifts (differences in average severity), while changes in the fitted slope summarize how cross-state dispersion differs wh en values are correctly separated from quantities.

We begin with supply-side GE propagation. For each sector-state pair, define GE amplification as

$$\hat{A}_{jr} = \hat{y}_{jr} - \hat{z}_{jr}, \tag{20}$$

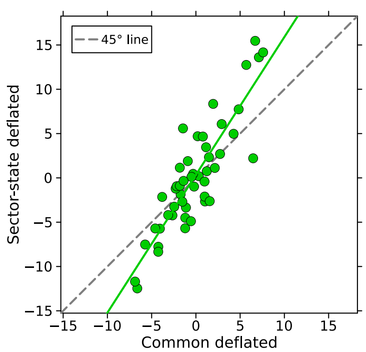
where $\hat{y}_{jr}$ is the peak-to-trough (or trough-to-peak) change in sectoral output and $\hat{z}_{jr}$ is the corresponding recovered productivity change required for the model to match that output path. Because $\hat{y}_{jr}$ is disciplined by construction, variation in $\hat{A}_{jr}$ reflects how the model attributes observed output movements between direct productivity wedges and endogenous propagation through factor adjustment, durable-stock and capital dynamics, and trade substitution. In the contraction, more negative values of $\hat{A}_{jr}$ indicate stronger amplification (output falls more than productivity), while in the recovery more positive values indicate stronger amplification (output rises more than productivity).

Figure 8 reports *Baseline*-*Alternative* comparisons of $\hat{A}_{jr}$ for agriculture (in green), manufacturing (in red), and services (in blue). Consider first the peak-to-trough contraction (top row). In agriculture, the fitted relationship is steep and rotates around values close to zero, indicating that correct deflation primarily increases the dispersion of GE amplification across states rather than shifting the average uniformly. Under the common-deflator *Alternative*, agricultural propagation is comparatively compressed, consistent with mismeasured quantity targets that mask substantial cross-state heterogeneity in how agricultural shocks transmit through the economy.

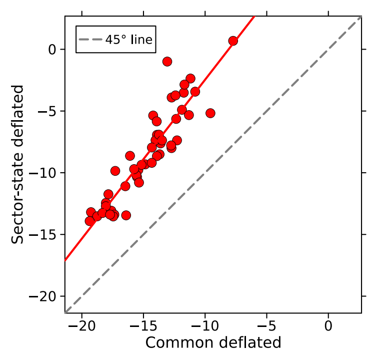
Manufacturing exhibits a different pattern. The fitted relationship lies systematically

Figure 8: **GE Amplifications by Sectors**

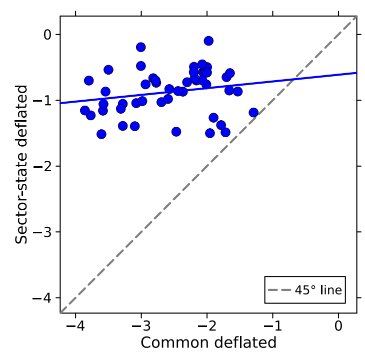
(a) Peak-trough: Agr.



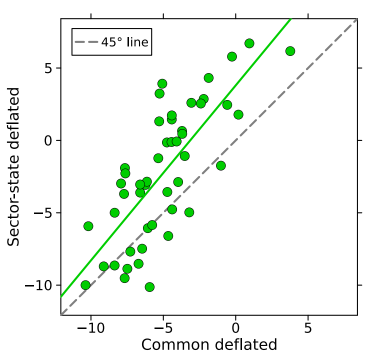
(b) Peak-trough: Man.



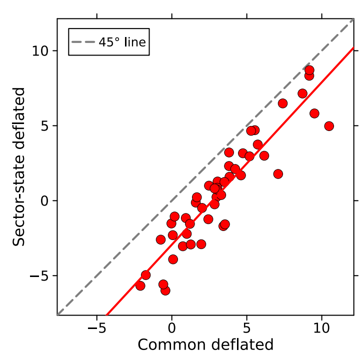
(c) Peak-trough: Ser.



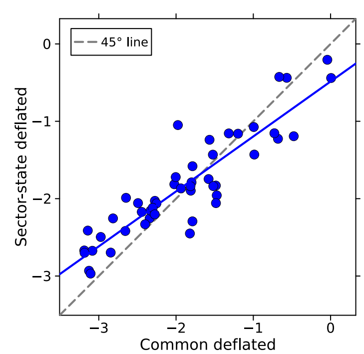
(d) Trough-peak: Agr.



(e) Trough-peak: Man.



(f) Trough-peak: Ser.



Note: Panels show sector-state general equilibrium amplification ($\hat{y}_{jr} - \hat{z}_{jr}$) under common versus sector-state deflation for contractions and recoveries.

above the 45-degree line over most of the states, implying that the *Baseline* delivers less negative amplification than the *Alternative* during the contraction. In other words, in the common-deflator *Alternative*, the model attributes a larger portion of manufacturing output declines to indirect GE propagation, whereas under correct deflation a larger share is absorbed by the direct recovered productivity component. At the same time, the slope of the fitted relationship is steeper under the *Baseline*, though not as steep as in agriculture, indicating that sector-state deflation generates greater cross-state dispersion and hence larger distributional differences in manufacturing outcomes.

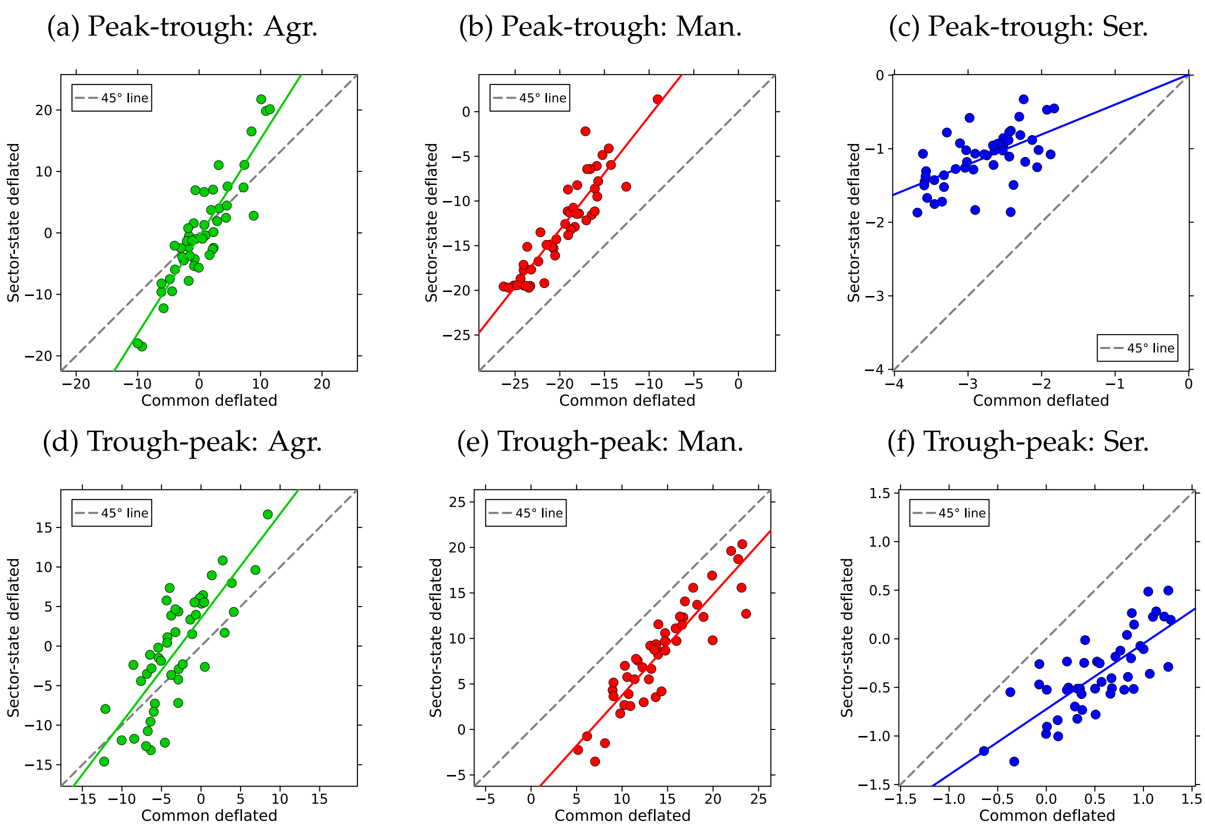
Services also display a noticeable level shift, but with much smaller dispersion than the traded sectors in both specifications. Moreover, dispersion is lower under the *Baseline* than under the common-deflator case, as reflected in the flatter slope, consistent with the limited scope for general equilibrium amplification in the non-traded service sector.

Turning to the trough-to-peak recovery (bottom row), agriculture continues to display sizable dispersion in $\hat{A}_{jr}$, indicating persistent cross-state heterogeneity in the strength of recovery-phase propagation. In manufacturing, the fitted relationship lies closer to (but below) the 45-degree line during the recovery, suggesting that measurement discipline remains similarly important for recovery dynamics in this sector when summarized by $\hat{A}_{jr}$. Services again show relatively muted effects in both levels and dispersion. Overall, agriculture emerges as the primary driver of cross-state heterogeneity in outcomes, while manufacturing plays the dominant role in shaping average general equilibrium propagation.

Figure 9 reports the labor response $\hat{h}_{jr}$ for sector-state workers during the contraction (peak-to-trough) and recovery (trough-to-peak), using the same visual structure as the preceding figure. Labor responses are informative because they are a direct endogenous propagation margin in the model: movements in hours contribute mechanically to $\hat{y}_{jr} - \hat{z}_{jr}$ and therefore to the GE amplification patterns documented earlier.

The agriculture panel exhibits the largest measurement-induced change in dispersion. The fitted relationship is steep, implying that correct deflation increases the cross-state spread of labor adjustments among agricultural workers relative to the

Figure 9: **Labor Response by Sectors**



Note: Panels show sector-state labor response under common versus sector-state deflation for contractions and recoveries.

common-deflator case. Notably, a subset of agricultural states displays positive labor responses during the contraction even when the real output declines. In the model, this reflects the standard tension between wealth and substitution effects: negative shocks reduce lifetime resources and can raise desired labor supply (wealth effect), while lower real wages can reduce desired hours (substitution effect). Which force dominates varies across agricultural states because the *Baseline* regime changes the inferred local shock mix and the associated equilibrium wage and relative-price movements.

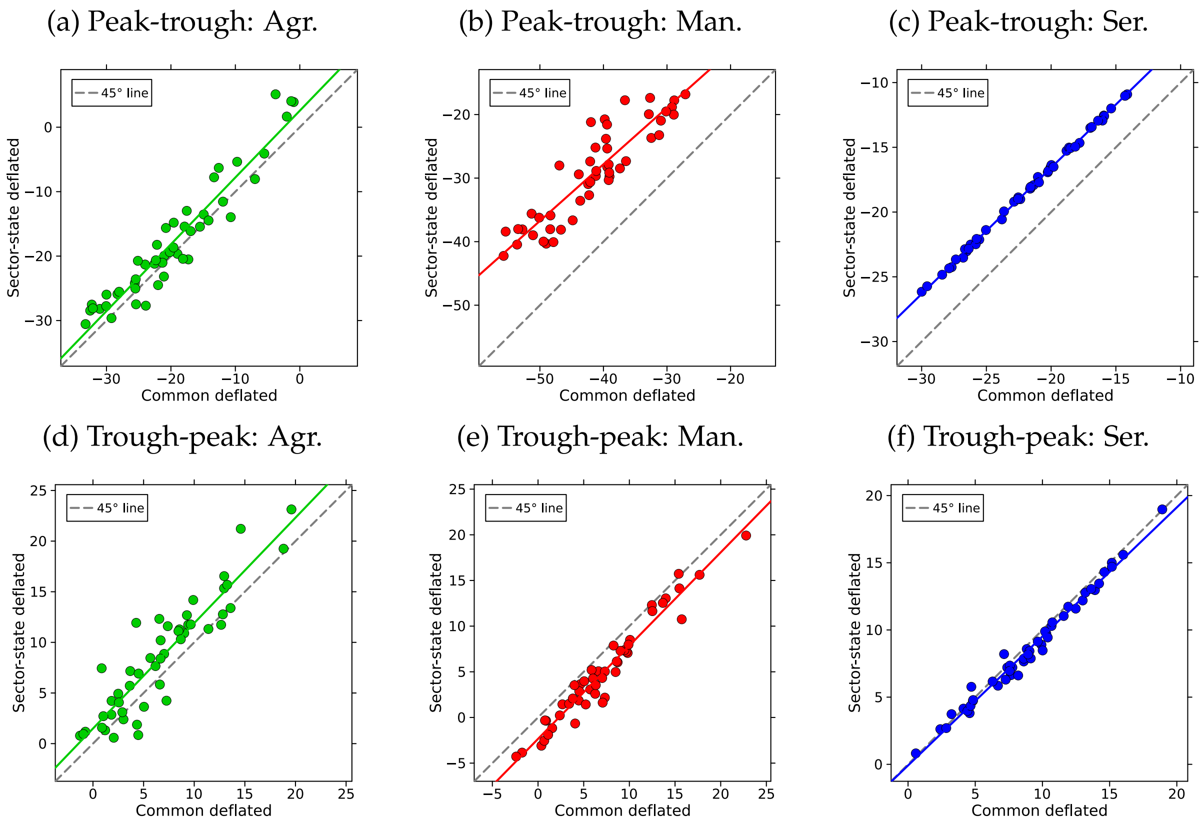
Manufacturing labor falls in almost all states during the contraction, consistent with durable-goods amplification and the sharp contraction in the traded durable sector. Relative to the *Alternative*, the *Baseline* scatter lies systematically above the 45-degree line, implying smaller average declines in hours under correct deflation. At the same time, the fitted relationship is steeper, indicating that correct measurement increases cross-state dispersion in manufacturing labor adjustments rather than simply shifting the mean.

Services display the smallest labor movements in magnitude. The *Baseline* outcomes are again above the 45-degree line, implying smaller labor contractions under correct deflation, but the slope is flatter than 45 degrees, indicating that correct measurement primarily acts to compress dispersion in service-sector labor. This is consistent with services being locally consumed and less exposed to the traded-sector terms-of-trade movements that drive heterogeneity in agriculture and manufacturing.

During the recovery, manufacturing and services are systematically below the 45-degree line, indicating that the common-deflator discipline implies a stronger labor rebound than the *Baseline*. Put differently, once quantities are correctly measured, the implied cyclical rebound in hours is more muted in these sectors, mirroring the broader pattern that mismeasured "quantities" exaggerate the amplitude of the cycle. Agriculture remains the sector with the largest dispersion in labor dynamics, with a steep fitted line and substantial cross-state heterogeneity in the pace of normalization.

We next examine the demand-side counterpart: consumption responses across sector-state agents. Figure 10 plots changes in total consumption for representative

Figure 10: **Agent Consumption Across Sectors**



Note: Panels show representative agent's consumption response in each sector-state under common versus sector-state deflation for contractions and recoveries.

agents indexed by sector j and region r. Beginning with peak-to-trough (top row), we find that points lie systematically above the 45-degree line across all sectors. This implies that correct deflation delivers smaller consumption losses than the common-deflator discipline. The effect is largest in levels for manufacturing: manufacturing agents exhibit the deepest consumption declines, consistent with the durable-goods and capital-adjustment mechanisms that magnify downturns in the traded durable sector. However, the comparison across deflator regimes is primarily a level correction as the fitted relationship is close to parallel to the 45-degree line. This indicates that correct deflation shifts the average severity of the manufacturing contraction without substantially reordering cross-state outcomes.

Agriculture shows a similar consumption-side pattern. While supply-side objects (e.g., GE amplification and hours) exhibit substantial cross-state heterogeneity in agriculture, consumption responses are comparatively unchanged and the main changes are limited to a level shift. This attenuation is consistent with the model's smoothing and trade structure: agents can smooth intertemporally through the national bond market, and traded-goods consumption is not mechanically tied one-for-one to local production. As a result, correcting deflation changes the level of agricultural consumption losses more than it changes their cross-state dispersion.

Services display the cleanest near-uniform shift. Consumption changes are tightly aligned along the fitted relationship, indicating that measurement has little effect on cross-state dispersion for service-sector agents. This pattern is consistent with services being locally provided and relatively evenly distributed across states: correcting traded-sector measurement affects service-sector consumption mainly through the aggregate general-equilibrium environment rather than through strongly state-specific channels.

During the recovery, outcomes cluster more closely around the 45-degree line, indicating that measurement matters less for consumption dynamics in the rebound than in the contraction. The sectoral pattern becomes asymmetric: agriculture remains modestly above the 45-degree line, implying slightly stronger consumption recoveries under correct deflation. In contrast, manufacturing and services lie slightly below the line, plying a more muted rebound under correct deflation. A natural interpretation is that the common-deflator discipline exaggerates the cyclical amplitude by loading relative-price normalization into measured “quantity” dynamics, whereas correct deflation yields smaller implied swings in real activity and therefore smaller consumption rebounds in manufacturing and services.

Taken together, the GE amplification, labor, and consumption results deliver three overarching messages. First, measurement matters beyond the targeted quantities. Moving from common (CPI) deflation to sector-state deflation changes the model’s implied business cycle propagation and incidence. In the scatter comparisons, measurement differences show up both as systematic level shifts (average severity) and as changes in cross-state dispersion (slope differences), implying that the welfare and distributional conclusions are sensitive to whether relative prices are correctly separated from quantities.

Second, the traded sectors shape the episode in distinct ways. In manufacturing, changes across deflation schemes are dominated by relatively parallel shifts across states, indicating that durable-goods and capital accumulation mechanisms primarily affect average severity. By contrast, agriculture is characterized by pronounced changes in dispersion: correcting deflation substantially increases cross-state heterogeneity in outcomes. Services, in turn, display largely uniform level shifts with limited changes in dispersion, consistent with their non-traded and geographically diffuse nature. Consumption responses are generally less dispersed, especially for households working in agriculture, reflecting tradability and intertemporal smoothing in decoupling local production shocks from local consumption more than from local labor or prices.

Third, measurement is most consequential in the contraction. Across sectors, peak-to-trough outcomes display larger deviations between *Baseline* and *Alternative* than trough-to-peak outcomes. Recoveries are more collinear across states, and relative-price and shock forces are less extreme as the economy reverts, so the measurement wedge plays a smaller quantitative role in the rebound than in the downturn.

6.3 Stochastic Gravity

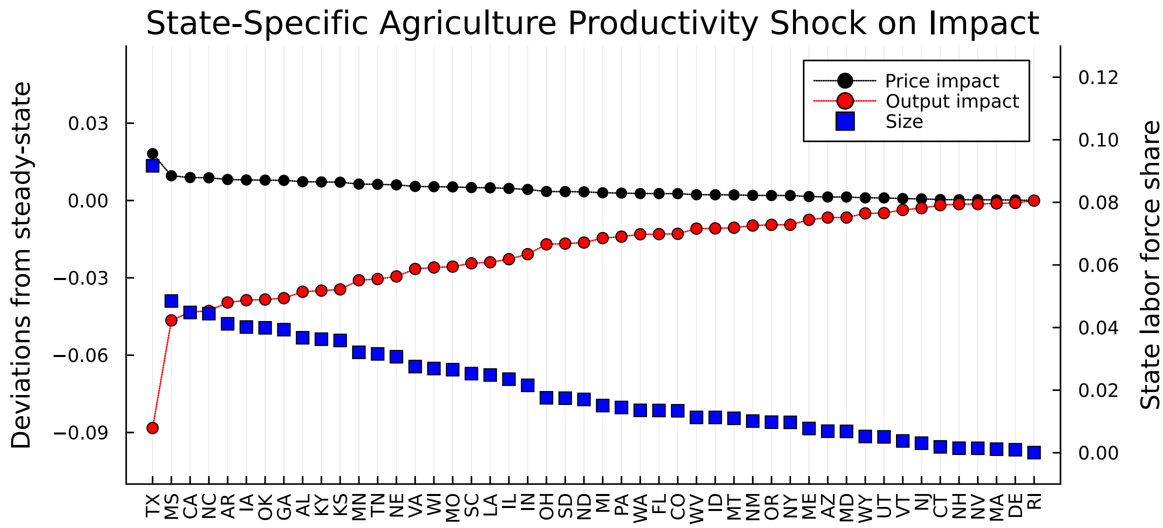
We now turn to the drivers of geographic heterogeneity in these results. In our framework, regional incidence is shaped by (i) economic size/specialization, which governs how strongly local shocks move aggregates, and (ii) the structure of the recovered productivity innovations. The next two exercises examine these channels: stochastic gravity maps sector-state shocks into movements in national sectoral prices and quantities, and the factor decomposition isolates how much of the observed dynamics requires sector-state shocks rather than common or sector-level components.

The preceding sections document large cross-state dispersion in sectoral outcomes and show that measurement affects both levels and dispersion through general-equilibrium propagation. We now aim to quantify a mechanism emphasized in the international business-cycle literature: stochastic gravity, the idea that the aggregate consequence of a local shock depends on the economic weight of the afflicted sector-location node (e.g., its employment/value-added share) and on within-sector substitution across varieties.

Toward this end, for each region r, we consider a one-percent negative productivity shock to a single sector-state pair, either agriculture (a, r) or manufacturing (m, r), holding all other innovations at zero. Using the model's (linearized) equilibrium mapping, we compute the response of (i) the national sectoral price index P^j and (ii) national sectoral output Y^j in the shocked sector $j \in \{a, m\}$. We report the impact effect (period-0 response). To connect these aggregate responses to economic size, each figure overlays the state's steady-state sectoral employment share, $\pi_{jr} / \sum_r \pi_{jr}$ (blue squares).

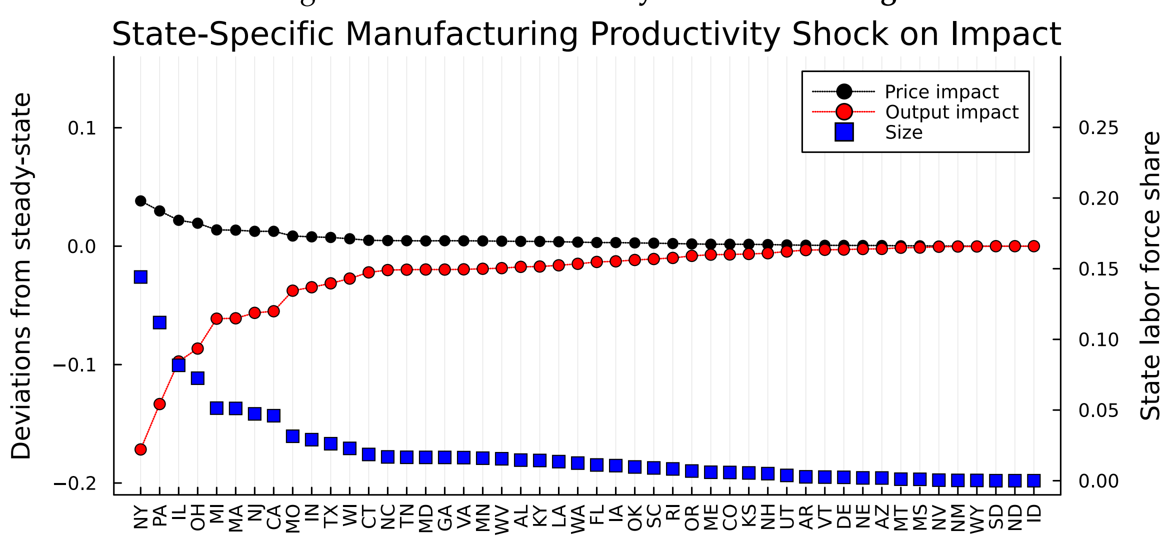
Figure 11 orders states by their agricultural employment shares and plots the resulting aggregate responses. Texas is the dominant agricultural node (about 9.2% of agricultural employment). A one-percent negative shock to Texas agriculture reduces national benchmark by roughly 0.09%, slightly less than the mechanical benchmark, $\pi_{ar} \times 1\% \approx 0.092\%$. The gap reflects general-equilibrium reallocation: other agricultural states expand production as expenditure and intermediate demand substitute across varieties. The national agricultural price index rises on impact, but by a comparatively

Figure 11: **Stochastic Gravity in Agriculture**



Note: The figure order U.S. states by agricultural employment shares (in blue square) and shows the resulting price (in black dot) and output (in red dot) responses to state-specific agriculture productivity shock.

Figure 12: **Stochastic Gravity in Manufacturing**



Note: The figure order U.S. states by manufacturing employment shares (in blue square) and shows the resulting price (in black dot) and output (in red dot) responses to state-specific manufacturing productivity shock.

small amount (on the order of a few basis points), consistent with high within-sector substitutability and offsetting supply responses elsewhere.

Figure 12 repeats the exercise for manufacturing shocks. Two patterns mirror agriculture: (i) aggregate effects decline monotonically with state size, and (ii) aggregate output responses are smaller in magnitude than the mechanical $\pi_{mr} \times 1\%$ benchmark because other states partially offset the shock. The key difference is the much stronger price response in manufacturing. Large manufacturing nodes, most notably New York (about 14% of manufacturing employment), generate pronounced increases in the national manufacturing price index even for the same one-percent shock. This reflects the model's durable-goods and capital structure: manufacturing varieties are not only consumed but also used to adjust stocks of durables and productive capital, amplifying the price effects relative to agriculture.

These experiments quantify a simple but powerful implication of the framework: economic size maps directly into aggregate consequences, but the mapping is attenuated by within-sector substitution and general-equilibrium reallocation. Stochastic gravity therefore provides a quantitative rationale for weighting sector-state shocks by π_{jr} in aggregation and clarifies why a small number of large nodes can matter disproportionately for national sectoral prices and quantities.

6.4 Factor Decomposition

Our shock-recovery procedure delivers a panel of productivity innovations $\{\epsilon_{jrt}\}$ that exactly reconciles the model with the targeted sector-state output paths. Under a first-order approximation, equilibrium allocations evolve according to linear state-space decision rules, so outcomes are linear in the innovation vector. This linearity allows us to run counterfactual simulations that restrict the dimensionality of the recovered innovations, without re-solving the model or re-estimating any parameters, by feeding alternative innovation sequences through the same decision rules. Using this property, we ask how much of the observed aggregate and cross-state quantity dynamics requires the sector-state-specific shocks.

We consider two alternative shock paths. Let π_{jr} denote the steady-state value-added (population) weight of section j in region r. First, the common-only innovation is the weighted average of recovered innovations across all sectors and states,

$$\epsilon_t^{\text{common}} = \sum_j \sum_r \pi_{jr} \epsilon_{jrt}. \tag{21}$$

The associated counterfactual sets $\epsilon_{jrt} = \epsilon_t^{\text{common}}$ for all (j, r), akin to a one-shock "aggregate efficiency wedge" in the spirit of business-cycle accounting in Chari et al. (2007). Second, the sector-only innovations aggregate within each sector,

$$\epsilon_{jt}^{\text{sector}} = \sum_r \pi_{jr} \epsilon_{jrt}, \tag{22}$$

and impose $\epsilon_{jrt} = \epsilon_{jt}^{\text{sector}}$ for all r within sector j, analogous to a multi-sector model with sectoral TFP shocks but no within-sector geography. We compare the resulting quantity dynamics under these counterfactual shock structures to those generated by the original specification, which allows for unrestricted ϵ_{jrt} and reproduces the targeted sector-state output paths by construction.

Table 3 reports the implied peak-to-trough (1929-1932) and trough-to-peak (1932-1935) percent changes in sectoral output quantities under each restriction, for both measurement regimes. Each cell reports the cross-state mean (aggregate incidence) and the cross-state standard deviation (geographic heterogeneity).

Let us first focus on Panel A. Two findings stand out. First, common-only shocks generate large sectoral contractions but essentially no cross-state dispersion: standard deviations are near zero in all sectors under both deflator regimes, several orders of magnitude smaller than the dispersion observed in the full state-sector shocks case. In other words, even a single aggregate innovation can produce some (but not all) asymmetry at the sectoral level but not across states. For example, manufacturing contracts more than agriculture under the *Baseline* (-31 percent vs. -22 percent) and *Alternative* (-40 percent vs. -29 percent) because the durable/capital structure amplifies the traded durable sector. However, by construction, a common shock cannot account for the pronounced cross-state heterogeneity that is central to our understanding of sectoral heterogeneity in the aggregate.

Second, sector-only shocks improve on common-only shocks by allowing average

Table 3: **Factor Decomposition - Quantity Changes by Deflator Regime**

	Baseline (sector×state deflators)			*Alternative* (common deflator)		
Scenario	Agr.	Man.	Ser.	Agr.	Man.	Ser.
Panel A: Peak-trough (1929-1932)						
Common-only shocks	-21.98 (0.21)	-30.62 (0.22)	-21.46 (0.33)	-28.62 (0.27)	-39.95 (0.28)	-27.88 (0.55)
Sector-only shocks	-6.32 (0.15)	-22.70 (0.15)	-23.64 (0.11)	-53.04 (0.32)	-39.46 (0.33)	-21.86 (0.70)
Full shocks (sector×state)	-10.83 (31.98)	-20.86 (16.81)	-22.60 (6.34)	-53.99 (16.34)	-38.78 (10.21)	-20.80 (6.49)
Panel B: Trough-peak (1932-1935)						
Common-only shocks	6.46 (0.11)	9.52 (0.11)	6.68 (0.73)	9.71 (0.10)	14.34 (0.10)	10.28 (0.51)
Sector-only shocks	6.71 (0.05)	12.52 (0.05)	6.57 (0.29)	34.80 (0.18)	23.75 (0.18)	1.80 (0.57)
Full shocks (sector×state)	8.07 (23.30)	9.33 (17.21)	7.43 (5.48)	33.76 (13.58)	22.61 (14.14)	2.47 (5.35)

Note: Each cell reports the cross-state mean percent change in sectoral output quantities over the stated phase, with the cross-state standard deviation in parentheses. *Baseline* targets quantities constructed using sector- and state-specific deflators. *Alternative* targets CPI-deflated series treated as quantities.

outcomes to differ across sectors, but they still generate almost no within-sector geographic dispersion. In this sense, multi-sector models disciplined only by sectoral aggregates miss a first-order feature of the Great Depression: heterogeneity within sectors across locations. Under the *Baseline*, the dispersion across states implied by sector-only shocks is approximately 0.15 percent in both agriculture and manufacturing and 0.11 percent in services - values comparable to those generated under common-only shocks. By contrast, allowing shocks to vary along both sectoral and geographic dimensions produces substantial dispersion: roughly 32 percent in agriculture, 17 percent in manufacturing, and 6 percent in services. Although the dispersion is somewhat smaller under the common-deflator scheme, the qualitative pattern remains unchanged.

Finally, the peak-to-trough contraction highlights how measurement affects the inferred sectoral shock composition. In the sector-only specification, the *Baseline* deflation implies only a modest agricultural contraction of about -6 percent. Under the *Alternative* common-deflator specification, however, the implied contraction in agriculture reaches -53 percent. Thus, treating CPI-deflated values as quantities does not simply alter model outcomes - it fundamentally changes the inferred sectoral shock mix by loading the terms of trade deterioration of agricultural producers into a large agricultural productivity collapse that did not, in fact, occur.

In sum, we find that the full sector-state innovations are necessary to reproduce cross-state dispersion. Under the *Baseline*, dispersion is especially large in agriculture, followed by manufacturing and then services. This echoes the earlier results: manufacturing drives much of the average contraction through durable-sector amplification, while agriculture is the dominant source of cross-state dispersion once quantities are correctly measured.

The recovery phase yields the same qualitative ranking. Common-only and sector-only shocks imply near-uniform recoveries within each sector, while the full sector-state shocks are required to generate the large dispersion observed in the data. The measurement contrast remains economically consequential: under the *Alternative*, the sectoral component implies extremely strong agricultural and manufacturing recoveries alongside a muted services rebound, whereas under the *Baseline* recoveries are more balanced across sectors. This, again, reflects that correct deflation removes large terms-of-trade distortions in the "quantity" measures and consequently allows more accurate inference about the underlying productivity shocks.

Taken together, Table 3 shows that low-dimensional shock structures (common-only and sector-only shocks) can generate substantial aggregate contractions and recoveries, consistent with the business-cycle accounting emphasis on efficiency wedges. But they generate essentially no cross-state income dispersion. Explaining the geographic incidence of the Great Depression therefore requires a framework that explicitly incorporates sector-state heterogeneity through differences in production structure and economic gravity.

Finally, our work helps to remediate an important data deficiency in the Great Depression era. Namely, the lack of sector-state deflators. Without these deflators, the sources of real and nominal income variation across states and sectors are impossible to measure or reconcile with existing economic theories.

7 Conclusion

This paper studies the distributional impact of the Great Depression across U.S. states through the lens of sectoral specialization and spatial general equilibrium. The motivating fact is that the Great Depression's severity varied enormously within the United States: state-level peak-to-trough contractions from 1929 to 1932 ranged from 15 percent to 48 percent - dispersion that is larger than the cross-country dispersion in many international comparisons. Explaining this heterogeneity requires both a sectoral perspective due to specialization and careful measurement of real quantities because relative prices in traded sectors moved sharply over time and unevenly across states.

Our first contribution is measurement. Using newly constructed sector- and state-specific deflators for agriculture and manufacturing, we show that CPI-deflated sectoral income series can misstate the underlying quantity dynamics. Agriculture provides the clearest illustration: in 1931 agricultural quantities rise even as nominal agricultural income falls, implying that the early contraction is largely a relative-price event rather than a physical production collapse. Treating CPI-deflated values as quantities therefore mechanically attributes terms-of-trade movements to "output," altering sectoral decompositions and the inferred shock composition.

Our second contribution is a quantitative framework that links specialization to propagation. In a 3-sector, 48-state dynamic stochastic general equilibrium model with traded agricultural and manufacturing varieties, durable-goods and investment channels, and non-traded services, we recover sector-state productivity wedges that exactly reproduce targeted sector-state quantity paths. This allows us to study untargeted equilibrium objects, particularly cross-state relative prices and the strength of general-equilibrium propagation, which are key for understanding the incidence of the Great Depression.

Our main quantitative findings are: (i) correct deflation changes the sectoral accounting of the Great Depression across state groups, reducing agriculture's apparent role in the aggregate contraction and recovery while highlighting durable-sector amplification in manufacturing; (ii) correct deflation improves the model's implied relative price dynamics, as shown by a substantially better fit to cross-state agricultural and manufacturing relative-price movements under the *Baseline* than under the common-deflator regime; and (iii) the cross-sectional dispersion of outcomes cannot be generated by low-dimensional shock structures (common-only or sector-only), implying that state-sector-specific shocks and their interaction with specialization are essential for explaining the distribution of losses.

These results have two broader implications. First, in episodes with large and heterogeneous relative-price movements, measurement regime is not merely a technical detail: it can reverse sectoral narratives and distort inference about the underlying shocks. Second, when production is spatially specialized and markets are incomplete, terms-of-trade are a first-order distributional channel, and regional business-cycle analysis should accordingly take this dimension into account.

Finally, our model's abstraction from several propagation mechanisms and shocks - including the dramatic collapse in stock prices, erratic movements in monetary aggregates, and rapidly deteriorating banking conditions - should not be interpreted as implying that these forces were unimportant, particularly given their role in the Global Financial Crisis and their likely relevance during the Great Depression. In our view, the novel measurement and deconstruction of the business cycle by sector and state undertaken in this paper is a necessary first step to introducing great model sophistication and the more daunting measurement challenges these extensions require. Much remains to be done.

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A Empirical Appendix

A.1 Aggregate U.S. Business Cycle

Table A.1: **Decomposition of Peak-to-Trough GDP movements**

	Great Recession			Great Depression		
NIPA Components	2008:1 Share	P-T % change	Contri-bution	1929 Share	P-T % change	Contri-bution
GDP	1.000	-0.034	1.000	1.000	-0.264	1.000
CD + I	0.234	-0.228	1.731	0.258	-0.699	0.685
CND + CS	0.610	-0.009	0.184	0.646	-0.159	0.389
G	0.201	0.049	-0.322	0.092	0.243	-0.085
X	0.122	-0.107	0.426	0.057	-0.549	0.118
M	0.169	-0.186	-1.020	0.053	-0.532	-0.107

Note: The table reports the decomposition of peak-to-trough GDP fluctuations during the Great Recession and the Great Depression. CD denotes consumer durables, CND denotes consumer nondurables, and CS denotes services.

Table A.1 provides a side-by-side comparison of these two U.S. business cycles with the goal of accounting for the respective contributions of each component of aggregate expenditure to the peak-to-trough declines in real GDP deflated by the GDP deflator during these two dramatic macroeconomic episodes. Notice that there is a statistical discrepancy in the NIPA accounts for the Great Recession which accounts for 10% of the peak-to-trough variation. This is distributed across NIPA components in proportion to their 2008:Q1 shares. Following the narrative by Hall (2010), consumer durables and investment are aggregated into one category of expenditure and consumer non-durables and services into another. Unlike Hall (2010), exports and imports are separately shown since the international trade collapse has featured prominently in both episodes.

Structurally, there are more similarities than differences across the two periods. Then, as now, non-durables and services accounted for the largest share of aggregate demand, 0.610 and 0.646, for the Great Recession and Great Depression, respectively. The next largest share is consumer durables and investment at 0.234 and 0.258, in the Great Recession and Great Depression, respectively. Notable differences across the two periods

Table A.2: **Sector Shares of State Income**

	Agriculture	Manufacturing	Services	Government
Mean	0.150	0.175	0.520	0.125
Median	0.154	0.167	0.519	0.119
First quartile	0.076	0.096	0.487	0.109
Third quartile	0.202	0.241	0.557	0.125
Inter-q range	0.126	0.145	0.070	0.016

are the much higher share of government spending in the present than in the past. Government spending is almost twice as high (0.201) during the Great Recession compared to the Great Depression (0.092). Trade shares are two to three times greater now relative to the interwar period.

Durables and investment fall sharply in both episodes, consistent with the narratives by Hall (2010) and Romer (1990). The similarities end there, however. Trade and the trade balance play a much larger role during the Great Recession whereas non-durables and services are virtually unaffected during the Great Recession, compared to a 15.9% decline during the Great Depression. This last observation points to the need for serious and detailed modeling of the role of agriculture in the Great Depression.

A.2 Additional Variance Decomposition Results

We begin with a depiction of production structure through the lens of sector level state income using the time-averaged share of income from sector (j) in total state (s) income, denoted as $\theta_{j,s}$. Table A.2 shows, on average, across U.S. states, services accounted for just over half of total income (0.520). Agriculture, manufacturing and government account for comparable shares of income, 0.150, 0.175 and 0.125, respectively. Note that since this is an income accounting identity (value added), the government share could be viewed as approximating the tax revenue necessary to finance government activities at the local, state and national level.

These average shares obscure important differences across the U.S. states. The income share distribution across states in terms of agriculture, manufacturing and services manifest core theoretical properties of the model that intersect the trade and macroeconomics literature. Essentially, the across-state within-sector share distribution is informative about comparative advantage and the potential for trade frictions to shape the spatial distribution of income by sector.

As is well understood, most services are difficult to trade across space in significant part because of the need (or utility value) of engaging in arms-length transactions between the producer and the consumer. Obvious examples of this are educational, medical and retail services. Consistent with this premise, the income share of services is very tightly concentrated about the mean (0.520) with an inter-quartile range of only 0.070.

In stark contrast, agriculture and manufacturing are much less tethered to population shares. The mean agricultural (manufacturing) share of state income is 0.150 (0.175) with an interquartile range of 0.126 (0.145).

By way of concrete examples, for agriculture, Delaware is has an agriculture income share close to the first quartile while Alabama is near the third quartile. For manufacturing, Texas is at about the first quartile, while North Carolina is at the third quartile.

During this period of history, the government provision of services skewed heavily toward state and local levels and thus like services tended to track population density. An obvious exception is the District of Columbia which accrued almost 40% of income from the government sector. While this might be viewed as a somewhat contrived example of the geographic concentration of federal government, it is also a reminder of the relevance of the denominator, that the District of Columbia has both a small population and geographic footprint leading to a somewhat exaggerated sense of specialization compared to the states. One could imagine that isolating on the geography of state capitals, particularly those that are not in highly agglomerated metropolitan centers would yield even greater skewness toward government services.

Table A.3 reports summary statistics for the standard deviation of sector-level income

Table A.3: **Standard Deviations of Growth Rates**

	Total	Agriculture	Manufacturing	Services	Government
		Panel A: Standard Deviations			
Mean	0.104	0.299	0.171	0.076	0.051
Median	0.096	0.268	0.161	0.076	0.047
First quartile	0.074	0.203	0.143	0.065	0.041
Third quartile	0.126	0.365	0.188	0.085	0.059
Inter-q range	0.052	0.162	0.045	0.020	0.017
		Panel B: Relative Standard Deviations			
Mean		2.796	1.792	0.792	0.560
Median		2.647	1.732	0.799	0.536
First quartile		2.254	1.558	0.660	0.358
Third quartile		3.197	1.998	0.886	0.689
Inter-q range		0.943	0.440	0.226	0.331

relative to that of total state income. The most volatile sector is agriculture with an average (across U.S. states) standard deviation of growth nearly 2.8 times that of total state income. The next most volatile sector is manufacturing with a *relative* standard deviation of 1.792. In contrast, private sector service incomes are relatively stable (0.792), though not to the level of the government sector (0.560).

The veracity of the business cycles in manufacturing and agriculture feature prominently in our quantitative business cycle analysis. The durability of manufactures lends itself to business cycle amplification through standard stock-flow arguments, both on the firm demand side via business investment and through the consumer demand side via durable goods such as automobiles. The agricultural sector is mostly ignored in the contemporary business cycle literature, because of its relatively small employment share in modern times. This does not hold for this historical period, particularly when examined at the state level of aggregation. Today, the county level of aggregation would show similar exposure across the rural geography. Since agricultural goods are perishable (or, at least, depreciate quickly in quality) and are subject to large sources of exogenous yield variation; this sector lends itself to instability of supply. Combined with the fact that most agricultural goods are necessities of sustenance leads to potentially large welfare consequences on both farmer and consumer sides of the equilibrium.

A.3 State-Level Agricultural Price Index Construction

The state-level micro-data on individual crops and livestock is an archive originally created by Cooley et al. (1977). The data are stored in a Troll database and cover a much longer historical period than used in this study. We extracted all the data and focus on the subset of data from 1929 to 1935 in order to overlap with main income data we utilize from Slaughter (1937).

Specifically, the data are drawn from the Agricultural Time Series-Cross Section Dataset, known as ATICS, based on the pioneering work by Cooley et al. (1977). The ATICS mainly collects data on acreage (e.g., acreage planted, and acreage harvested), farm price, and quantity of production at the state level for 18 crops and 4 livestock, in addition to climate data such as temperature and rainfall. The variables we focus on in this study are farm price and quantity of production, and the product of the two generates the value of product. We will compare the ATICS price data with CPI data from the Bureau of Labor Statistics (BLS) when constructing real agriculture income using nominal agriculture income data from Slaughter (1937).

With all 18 crops and 4 livestock, our data has 7392 observations. However, to match the fact we only use crops to construct agricultural price index by state and year that is used in the paper, we focus on 18 crops (more accurately 16 crops as Tame Hay and Peanuts have no observations in the sample, see Table A.4 below). This reduces the observations 6048 observations and constitutes our benchmark ATICS sample. Our ATICS sample spans across 48 states and over the period of 1929-1935. The list of crops included in the benchmark sample is presented in Table A.4.

We construct the agricultural price index using crops only, excluding livestock. The

Table A.4: **Production Income Shares by Crop**

Crops	Production Income shares	Crops	Production Income shares
Corn	37.14%	Rice	0.83%
Cotton	18.40%	Flaxseed	0.60%
Wheat	14.11%	Soybeans	0.51%
Oats	8.77%	Rye	0.49%
Potatoes	7.21%	All Hay	0.21%
Tobacco	5.66%	Hops	0.16%
Barley	2.73%	Buckwheat	0.14%
Sweet Potatoes	1.57%	Tame Hay	0.00%
Sugar Beets	1.46%	Peanuts	0.00%

Note: The production income shares are the share of value of product, i.e., the ratio of the value of product of each crop to the total value of product of all crops. The value of product is calculated as the sum across all years and states, by crop for the numerator and across all crops for the denominator. For the period of 1929-1935, there are no observations for Tame Hay and Peanuts in our sample, so the shares are basically zeroes.

main reason is that, unlike crops, livestock represents a stock variable rather than a flow, which requires additional adjustments to incorporate it properly into the index. Such adjustments are not readily available in the historical data, and we leave this extension to future research.

To construct agriculture price index using our ATICS sample, we first construct nominal agriculture income by year and state in two steps.

- *Step 1.* For each of the 18 crops by year and state, multiply price and quantity to get value by year and state: $V_{c,j,t} = P_{c,j,t} * Q_{c,j,t}$, where c denotes farm product (18 crops), j denotes state, and t denotes year.

- *Step 2.* For each state, aggregate values across all farm products by year to obtain nominal agriculture income by year: $V_{j,t} = \sum_{c=1}^{18} V_{c,j,t}$, where $V_{j,t}$ denotes the nominal agriculture income by year and state constructed from ATICS.

Then, agriculture price index by year and state is constructed in the spirit of Laspeyres price index in four steps.

- *Step 1.* For each of the 18 crops by state, calculate its initial production income share in total state agriculture income using 1929 data as: $w_{c,j,0} = V_{c,j,0}/V_{j,0}$, where 0 denotes the initial year of 1929. $w_{c,j,0}$ will be used as weights to construct agriculture price index by year and state.

- *Step 2.* For each of the 18 crops by state and year, calculate its weighted price as $P^{w}_{c,j,t} = w_{c,j,0} * P_{c,j,t}$.
- *Step 3.* For each state by year, aggregate the weighted prices across farm products to obtain the aggregate price for a basket of farm products (i.e., 18 crops) at the state level by year: $P^{w}_{j,t} = \sum_{c=1}^{18} P^{w}_{c,j,t} = \sum_{c=1}^{18} w_{c,j,0} * P_{c,j,t}$.
- *Step 4.* For each state by year, normalize the aggregate price obtained in Step 3 into an agriculture price index so that its value in 1929 is 100 for all states: $PI_{j,t} = P^{w}_{j,t}/P^{w}_{j,0} * 100$, where 0 denotes the initial year of 1929, and $PI_{j,t}$ denotes the agriculture price index for state j at time t.

A.4 State-Level Manufacturing Price Index Construction

The Census of Manufacturing does not provide adequate coverage of unit values at the product level needed to construct manufacturing price deflators at the state level. Our approach is to use a newly digitized panel of annual export unit values (*Foreign Commerce and Navigation of the United States*, 1927-1935) and combined with state-by-sector value-added totals (Census of Manufactures, 1929). The construction proceeds in three steps: classifying products into ten common groups (Export-10) based on *Foreign Commerce and Navigation of the United States* classification, computing state exposure weights, and building sector and state price indices using constant-1929 weights.

A.4.1 Data Sources and Sector Classification

We digitize annual U.S. export tables from *Foreign Commerce and Navigation of the United States*, drawing on tables titled "Exports of domestic merchandise from the

United States, by articles and countries, during the calendar year [year]." Each record contains export value, quantity, reported units, and a product identifier. Identifiers are harmonized into time-consistent codes and units are standardized to obtain a panel over 1927-1935. State exposure weights are constructed from state-by-sector value-added totals from the 1929 Census of Manufactures (CoM).

Each export product is assigned to one of ten Export-10 groups via its product code, using the code ranges in Table A.5. CoM sectors are mapped to the same groups using the crosswalk in Table A.6.

Table A.5: Export-10 groups: raw code ranges

Export-10 group	Code range
Group 0. Animals and Animal Products†	10–999
Group 1. Vegetable Food Products and Beverages	1011–1779
Group 2. Other Vegetable Products, Except Fibers and Wood	2011–2999
Group 3. Textiles	3000–3999
Group 4. Wood and Paper	4006–4799
Group 5. Nonmetallic Minerals	5001–5999
Group 6. Metals, and Manufactures, Except Machinery and Vehicles	6001–6999
Group 7. Machinery and Vehicles	7000–7999
Group 8. Chemicals and Related Products	8002–8799
Group 9. Miscellaneous	9000–9999

† The original *Foreign Commerce and Navigation of the United States* classification distinguishes "Animals and animal products, edible" from "Animals and animal products, inedible"; these two groups are consolidated here.

A.4.2 State Exposure Weights

Let $X_{s\ell,1929}$ denote value added in state s and CoM sector ℓ in 1929. We aggregate to the Export-10 level as $X_{sg,1929} \equiv \sum_{\ell \in \mathcal{L}(g)} X_{s\ell,1929}$, where $\mathcal{L}(g)$ is the set of CoM sectors mapped to group g (Table A.6). State exposure shares are then

$$\theta_{sg,1929} \equiv \frac{X_{sg,1929}}{\sum_{g'=0}^{9} X_{sg',1929}}, \qquad \sum_{g=0}^{9} \theta_{sg,1929} = 1,$$

Table A.6: Crosswalk of Census of Manufacturing Sectors to Export Sectors

No.	CoM sector	No.	Export-10 group
1	Leather and its manufactures	0	Animals and animal products
2	Food and kindred products	1	Vegetable food products and beverages
3	Rubber products	2	Other vegetable products, except fibers and wood
4	Textiles and their products	3	Textiles
5	forest products	4	Wood and paper
6	printing, publishing, and allied industries	4	Wood and paper
7	Products of petroleum and coal	5	Nonmetallic minerals
8	Stone, clay, and glass products	5	Nonmetallic Minerals
9	Iron and steel and their products, not including machinery	6	Metals and manufactures, except machinery and vehicles
10	Nonferrous metals and their products	6	Metals and manufactures, except machinery and vehicles
11	Machinery, not including transportation equipment	7	Machinery and vehicles
12	Transportation equipment, air, land, and water	7	Machinery and vehicles
13	Chemicals and allied products	8	Chemicals and related products
14	Miscellaneous industries	9	Miscellaneous

and are held fixed at their 1929 values for all years.

A.4.3 Price Index Construction

Let $t \in \{1927, \ldots, 1935\}$, i a time-consistent product, and $g \in \{0, \ldots, 9\}$ an Export-10 group. Collapsing across destination countries, the product-year unit value is $p_{it} \equiv V_{it}/Q_{it}$, restricted to $Q_{it} > 0$ and $p_{it} > 0$.

Common-support basket. We retain only products observed in every year 1927–1935 under a single unit of measurement.

Sector indices. Let Ω_g denote the common-support products in sector g, with constant base-year value shares

$$w_{ig}^{1929} \equiv \frac{V_{i,1929}}{\sum\limits_{j \in \Omega_g} V_{j,1929}}.$$

The sector-level price index is the 1929-weighted geometric mean of unit values, rebased to 100 in 1929:

$$\widetilde{P}_{gt}^{1929} \equiv 100 \times \frac{\exp\left(\sum_{i \in \Omega_g} w_{ig}^{1929} \log p_{it}\right)}{\exp\left(\sum_{i \in \Omega_g} w_{ig}^{1929} \log p_{i,1929}\right)}.$$

State and aggregate indices. The state-level and U.S. aggregate indices are computed as *arithmetic* weighted averages of the rebased sector index numbers. Specifically,

$$\widetilde{P}_{st}^{1929} \equiv \sum_{g=0}^{9} \theta_{sg,1929}\, \widetilde{P}_{gt}^{1929},$$

and the U.S. aggregate uses national sector shares ω_g (each group's share of total national manufacturing value added in 1929),

$$\widetilde{P}_{US,t}^{1929} \equiv \sum_{g=0}^{9} \omega_g\, \widetilde{P}_{gt}^{1929}, \qquad \sum_{g=0}^{9} \omega_g = 1.$$

Archival sources:

- U.S. Bureau of Foreign and Domestic Commerce. *Foreign Commerce and Navigation of the United States*, annual volumes, 1927-1935. Washington, D.C.: Government Printing Office.
- U.S. Bureau of the Census. *Census of Manufactures, 1929*. Washington, D.C.: Government Printing Office, 1933.

B Model Appendix: Details on Solving the Model

First, we review how *Crucini residuals* are constructed in a one sector neoclassical model. Let $\hat{y}_t$ and $\hat{k}_t$ be log deviations of output and capital from its steady state values, respectively. Then, the linearized decision rule for output can be written as

$$\hat{y}_t = \gamma_k \hat{k}_t + \gamma_z \hat{z}_t, \tag{A.1}$$

where γ_k and γ_z are functions of deep parameters of utility, production, and persistence of the productivity shock. Given capital and output data, we can analytically solve for $\hat{z}_t$, which can be written as

$$\hat{z}_t = \frac{\hat{y}_t - \gamma_k \hat{k}_t}{\gamma_z}. \tag{A.2}$$

γ_z and γ_k are functions of the persistence of the shock, ρ_z. Thus, we get a new estimate for the persistence, $\tilde{\rho}_z$, using the recovered $\hat{z}_t$ from the previous equation. We re-calculate linear decision rule coefficients that reflects the new persistence of the shock, and solve it iteratively until the persistence estimate converges.

This method cannot be directly applied in our setting due to data limitations. We would need data on capital at the sector-state level, which do not exist yearly. To overcome this limitation, we pursue a modified approach. We guess a sequence of $\epsilon^0_{jr,t}$ for all region r and sector j. Assuming that the economy was in steady state on and before 1929, we can solve for $y^{model}_{rj,t}$ by feeding in the productivity shocks to the linearized model. Afterwards, we use $y^{data}_{rj,t}$ to get a new guess of productivity shocks, $\epsilon^1_{rj,t}$. The updating rule is

$$\epsilon^1_{rj,t} = \epsilon^0_{rj,t} + \phi(y^{model}_{rj,t} - y^{data}_{rj,t}), \tag{A.3}$$

where ϕ is set to 0.1. We stop when $\max\{|\epsilon^1_{rj,t} - \epsilon^0_{rj,t}|\}$ is below 1e$-$8. The productivity paths can be backed out from the VAR(1) from the estimated shocks, $\epsilon_{rj,t}$. We make an assumption for now that the off-diagonals of productivity shock matrix are 0, and get a new estimate for the productivity persistence and continually update the persistence parameter for each shocks until convergence.