# Financial Deepening, Investment Producers, and the Great Moderation*

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**Abstract**

During the Great Moderation, employment volatility plummeted while financial volatility rose sharply. We show that changes within the manufacturing sector were disproportionately responsible for both patterns and provide causal evidence linking these effects to improved access to capital markets ("financial deepening"). To explain our findings, we construct a multi-sector model featuring input-output linkages and financially constrained producers. Easing financial constraints in the model parsimoniously replicates the aggregate and sector-specific changes in both real and financial volatility observed during the Great Moderation. Our results highlight the importance of investment-producing sectors in understanding how financial frictions distort real activity.

*JEL Classification*: E22, E32, E52
*Keywords*: Great Moderation, investment, financial constraints

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# 1 Introduction

Since the mid-1980s, the volatility of output, employment, and prices in the US has declined dramatically. This phenomenon has been termed the "Great Moderation", and its causes remain the subject of considerable debate. In this paper, we argue that technological and regulatory developments in the financial sector—a process known as "financial deepening"—played a crucial role in the Great Moderation by easing financial constraints, and that this channel operated primarily through the manufacturing sector.

Our approach is motivated by the fact that, as first documented in Jermann and Quadrini (2009), firms' balance sheets became *more* volatile during the Great Moderation even as most indicators of real activity became *less* volatile. After constructing novel balance sheet measures for the aggregate manufacturing and nonmanufacturing sectors, we use a statistical decomposition to show that the manufacturing sector was primarily responsible for both the decreasing volatility of real activity and the increasing volatility of financial activity despite comprising small shares of aggregate output and employment. Existing work, which primarily analyzes the Great Moderation through the lens of single-sector models with no financial frictions, cannot simultaneously explain these facts.

To understand the direction of causality underlying these findings, we exploit state-level variation in credit supply resulting from staggered deregulation of US interstate banking restrictions in the 1980s. Past work such as Morgan, Rime, and Strahan (2004) showed that this exogenous expansion in credit supply led to reductions in the volatility of state-level output and employment. Consistent with our aggregate evidence, we find that states with larger manufacturing sectors experienced larger declines in volatility. The marginal effect of a one standard deviation increase in a state's manufacturing employment share prior to deregulation represents 11% of the total post-GM decline in the average magnitude of cyclical fluctuations for employment and 42% for output, suggesting that the manufacturing sector served as an important channel through which the easing of financial frictions reduced volatility.

We rationalize these findings using a multisector model that combines input-output production linkages with the financial frictions developed in Jermann and Quadrini (2012). In the absence of these frictions, firms can perfectly offset purely financial shocks by adjusting the composition of debt and equity while leaving production decisions unchanged. However, if firm balance sheets cannot costlessly absorb these shocks, nonfinancial variables will be forced to adjust instead. Because shocks originating entirely within the financial sector are an important source of business cycle variation in output, employment, and investment in the model, changes in the severity of firms' financial frictions can have a large impact on the dynamics of real activity.

Sectoral heterogeneity is crucial for understanding how changes in financial structure affect the transmission of shocks in the model. As in the data, the manufacturing sector in our model produces most of the economy's investment goods. Demand for these long-lived capital goods is more sensitive to financial shocks than demand for nondurable goods, causing employment and output in the manufacturing sector to exhibit larger responses to financial shocks. The most quantitatively important consequence of reducing firm financial constraints in the model is to allow the manufacturing sector to absorb these shocks almost entirely by adjusting the composition of debt and equity, rather than adjusting output and employment. While easing financial constraints also reduces nonmanufacturing volatility, the impact on aggregate volatility is much smaller because financial shocks have much smaller effects on nonmanufacturing firms. This channel can explain why the model's manufacturing sector is primarily responsible for generating both a *decrease* in the volatility of real variables and a simultaneous *increase* in the volatility of financial variables in response to easing financial constraints.

Our results have two important implications for researchers and policymakers. First and foremost, a better understanding of underlying drivers of the Great Moderation can yield insights into whether its effects should be expected to continue. To the extent that firm access to capital markets has continued to improve over time, we would not expect the contribution of financial deepening to reduced nonfinancial volatility to be transitory. Second, unlike exogenous changes in the distributions of fundamental shocks—which by definition are outside of policymakers' control—our results suggest that policies designed to improve firms' access to capital markets can lead to a first-order reduction in the magnitude of business cycle fluctuations. The fact that the effects of financial deepening come disproportionately from a small set of investment producers can help inform the design of policies meant to improve capital market access. For example, our model suggests that reducing financial frictions only for manufacturing firms reduces the peak effect of a financial shock on real investment by 2/3; in contrast, reducing them only for nonmanufacturing firms has virtually no effect on investment.

**Literature review.** These results build on the substantial body of literature analyzing the causes and consequences of the Great Moderation, which was first documented in Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and Blanchard and Simon (2001). While the stylized facts that define the Great Moderation are well known, the literature remains divided into two broad camps on its causes. One class of explanation, first advanced in the "good luck hypothesis" of Stock and Watson (2002), is that the distribution of structural shocks hitting the economy changed starting in the mid-1980s. The second class of explanation argues that it is not the distribution of shocks that changed over time, but rather their propagation. One prominent example of this is the "good policy" hypothesis advocated by Lubik and Schorfheide (2004) and Coibion and Gorodnichenko (2011), who argue that the Great Moderation was driven by improved policy making on the part of the Federal Reserve.

By emphasizing the role of changing financial frictions for investment producers, this paper falls primarily into the second category, and thus complements past empirical work arguing for the importance of changing financial frictions such as Dynan, Elmendorf, and Sichel (2006) and Grydaki and Bezemer (2013). However, our results can also be thought of as providing a structural interpretation for why the distributions of shocks might have changed. For example, while Justiniano and Primiceri (2008) find that investment-specific technology shocks are quantitatively important drivers of changes in business cycle volatility, they suggested that these shocks could also be proxies for unmodeled financial frictions. Rather than focusing on a specific interpretation, they conclude that "efforts to understand the Great Moderation should focus on the dramatic changes in the investment equilibrium condition." Our paper takes exactly this approach and finds that investment-producing sectors are the primary beneficiaries of easing financial frictions. By focusing on sectoral heterogeneity, our work also complements recent work such as Foerster, Sarte, and Watson (2011), Garin, Pries, and Sims (2018), and Vom Lehn and Winberry (2022), who show that changes in the distributions of sector-specific shocks led to changes in the properties of business cycles over the past several decades.

Lastly, this paper builds on the literature documenting the importance of financial shocks in driving real activity. Our primary theoretical contribution is to incorporate the financial frictions used in Jermann and Quadrini (2009) and (2012) into a multisector model. We first develop several novel empirical measures of financial activity for the manufacturing sector, which we use to discipline our theoretical approach. In addition to yielding new insights about the importance of sectoral heterogeneity in the transmission of financial shocks in this class of models, our framework also sheds light on how changes in financial frictions can affect the transmission of other shocks.

The paper proceeds as follows. Section 2 provides background on—and documents manufacturing's oustsized role in driving—the Great Moderation. Section 3 provides causal evidence for the importance of the manufacturing sector in the transmission of financial deepening to volatility using interstate banking deregulation as a natural experiment. Section 4 develops a multisector model with heterogeneous financial constraints to analyze the quantitative implications of easing firm financial frictions. Finally, section 5 concludes with a discussion of the implications of our findings for researchers and policymakers.

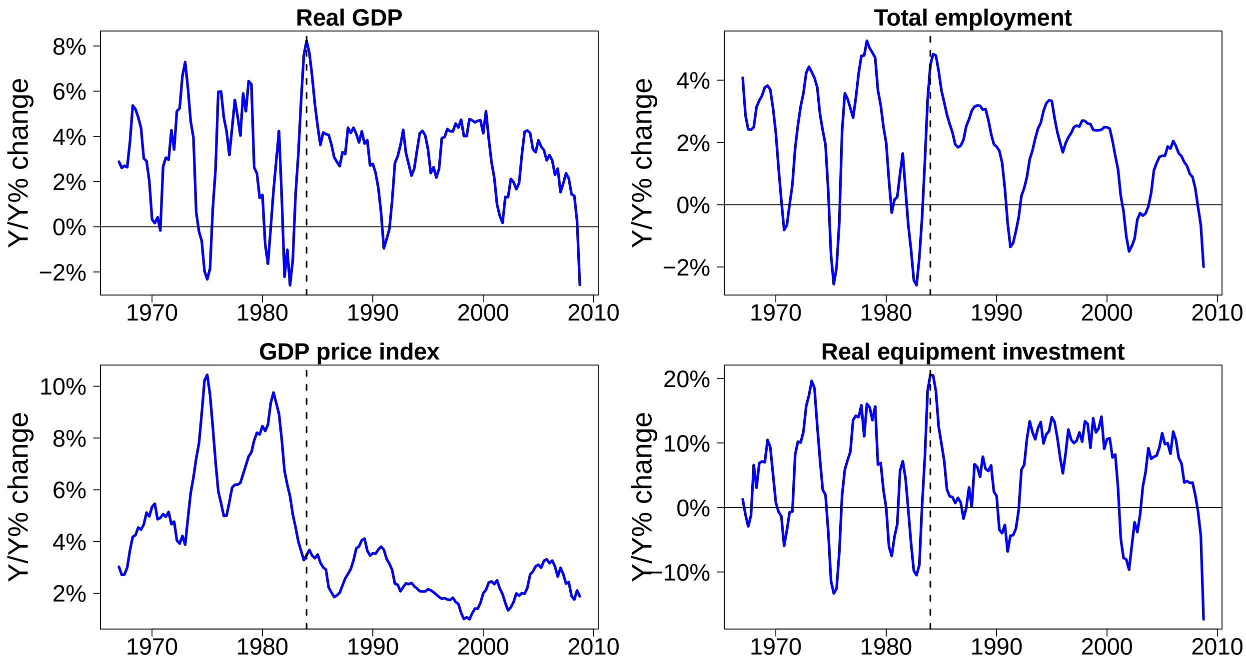


Figure 1: Annual growth rates of economic aggregates

*Notes:* This figure plots the year-over-year percent change in the real GDP, total nonfarm payroll employment, the GDP price index, and real equipment investment from 1967 through 2008. The dashed vertical line corresponds to the first quarter of 1984, which is marked as the start of the Great Moderation in McConnell and Perez-Quiros (2000).

# 2 The Great Moderation

## 2.1 Background

The volatility of most U.S. nonfinancial macroeconomic time series declined substantially starting in the mid-1980s. This reduction in volatility can be seen in figure 1, which plots annual growth rates for GDP, employment, prices, and equipment investment. The vertical dashed line in each figure marks the first quarter of 1984, which is the date of the structural break identified in McConnell and Perez-Quiros (2000). Each of these series shows a marked reduction in volatility in the post-1984 period.

Further evidence is shown in table 1, which reports the average magnitude of cyclical fluctuations for several key macroeconomic time series before and after this cutoff date using the filter of Hamilton (2018). The first three columns show that the decline in the

Table 1: Magnitude of cyclical fluctuations over time

| | GDP | Consumption | Fixed investment | Prices | Employment |
|---|---|---|---|---|---|
| Entire sample | 2.51 | 2.07 | 7.72 | 1.68 | 2.07 |
| Pre-1984 | 3.32 | 2.71 | 8.43 | 2.79 | 2.68 |
| Post-1984 | 2.03 | 1.68 | 7.30 | 1.02 | 1.70 |

*Notes:* This table shows the average absolute value of the cyclical fluctuations for real GDP, real personal consumption expenditure, real nonresidential fixed investment (including structures, equipment, and intellectual property products), the GDP price index, and total employment. These values are obtained from applying the Hamilton (2018) filter to the log of each series and then multiplying by 100. The top row reports values across the entire sample (1969-2008). The middle row includes values from 1969-1983. The bottom row includes values from 1984-2008.

volatility of real GDP fluctuations was driven by both consumers and businesses. The fourth and fifth columns show similar reductions in the average magnitude of cyclical deviations for prices and employment. Taken together, these patterns suggest a broad-based decline in nonfinancial activity.

While this pattern was observed to varying degrees across most nonfinancial variables, Jermann and Quadrini (2009) show that many financial variables became more volatile after 1984. This can be seen in figure 2 below, which plots four-quarter changes in the total value of debt, equity, and gross dividend payments for the nonfinancial corporate business sector as a share of nominal GDP. In contrast to the patterns observed in nonfinancial variables in figure 1, the series in this figure become markedly more volatile after the onset of the Great Moderation. This divergence in the behavior of real and financial variables poses a challenge for theories of the great moderation that rely entirely on changes in the distributions of shocks; in the commonly used setting of linearized models with uncorrelated shocks, for example, reducing the variance of any individual shock while holding all others fixed will necessarily lead to a weakly lower variance for all endogenous variables.

In the rest of this section, we document that the manufacturing sector was the primary

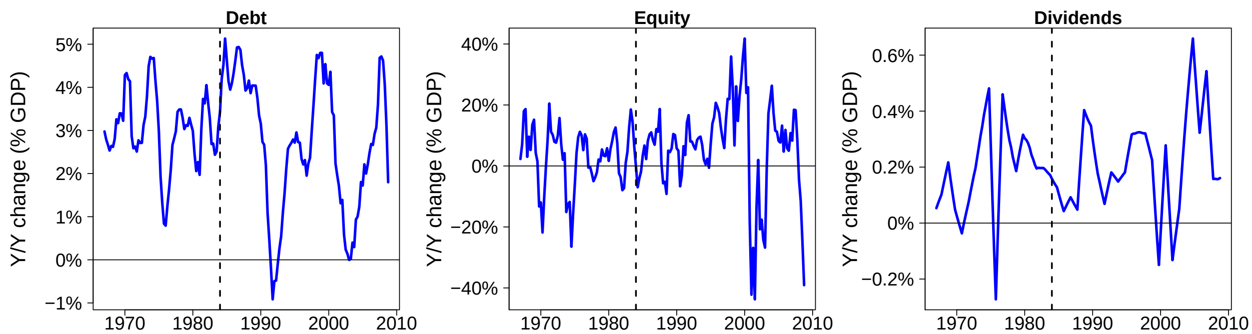


Figure 2: Changes in financial variables

*Notes:* This figure plots the year-over-year change in the value of debt, equity, and gross dividends (expressed as a share of nominal GDP) for nonfinancial corporate business from 1967 through 2008. Debt and equity come from the US financial accounts while net dividends come from the NIPAs. The dashed vertical line corresponds to the first quarter of 1984, which is marked as the start of the Great Moderation in McConnell and Perez-Quiros (2000).

driver of changes in both real and financial volatility since the Great Moderation. The outsized role of manufacturing in driving nonfinancial volatility is well documented[1], but to our knowledge, our paper is the first to provide direct evidence of its importance in driving changes in financial volatility. Our emphasis on the manufacturing sector is consistent with several proposed mechanisms that describe the Great Moderation through the lens of structural changes in the nature of aggregate activity, when in reality many of these changes took place primarily (or even exclusively) within the manufacturing sector. For example, while McConnell and Perez-Quiros (2000) argue for the importance of inventories, their empirical exercises find "a causal role for changes within the durable goods sector in stabilizing the aggregate economy". Explanations that find an important role for investment-specific technology shocks, such as Justiniano and Primiceri (2008), are also fundamentally about manufacturers given the unique importance of the manufacturing sector in producing investment goods documented in Vom Lehn and Winberry (2022).

[1] As one example, Ramey and Vine (2006) show that motor vehicle manufacturing alone accounts for almost 25% of the volatility of real GDP growth despite an average GDP share of less than 5%.

## 2.2 Manufacturing and employment volatility

In this section, we use a variance decomposition to argue that changes within the manufacturing sector alone can account for the majority of the decline in employment volatility during the Great Moderation.[2] While some of this effect can be attributed to manufacturing's shrinking share of employment over the past several decades, we find that the decline in the volatility of manufacturing employment was quantitatively far more important.

To account for the changing composition of employment across sectors over the past several decades, we define the change in *fundamental* volatility as the change in total variance that would have occurred had the manufacturing share remained fixed at its pre-Great Moderation level. We then use a simple linear decomposition to attribute the change in this fundamental volatility to changes in the volatility of each sector. Using this approach, we find that manufacturing accounted for almost two-thirds of the decline in fundamental volatility, which in turn accounted for almost 90 percent of the total decline in volatility. This result is especially striking since manufacturing made up less than one quarter of all employment in the pre-Great Moderation sample.

We begin by writing aggregate employment as the sum of manufacturing and nonmanufacturing employment: $A = M + N$. Using $\Delta$ to denote growth rates, we express the percentage change in aggregate employment $\Delta A$ as a weighted average of employment growth in each sector: $\Delta A = \gamma \Delta M + (1-\gamma)\Delta N$, where $\gamma$ is the manufacturing employment share. From this expression, the variance of $\Delta A$ is

$$Var(\Delta A) = Var(\gamma \Delta M) + Var((1-\gamma)\Delta N) + 2Cov(\gamma \Delta M, (1-\gamma)\Delta N). \tag{1}$$

[2] We focus on employment for this exercise because it is consistently and reliably measured over a long history for both the manufacturing and nonmanufacturing sectors, which allows us to calculate sectoral contributions to aggregate changes in real activity that do not involve prices. While it is possible to find alternative measures of real activity such as GDP by industry, they are derived from nominal expenditure data using chain-weighted price indices, and thus will not sum to aggregate real GDP.

Because $\gamma$ changes over time and is not independent of the growth rates $\Delta M$ and $\Delta N$, attempts to further decompose this expression will introduce many unwieldy higher-order terms.[3] However, a tractable approximation obtains if we assume $\gamma$ is a constant $\bar{\gamma}$:

$$Var(\Delta A) \approx (\bar{\gamma})^2 Var(\Delta M) + (1-\bar{\gamma})^2 Var(\Delta N) + 2\bar{\gamma}(1-\bar{\gamma})Cov(\Delta M, \Delta N) \equiv \widehat{Var}(\Delta A). \tag{2}$$

Our goal is to decompose these total changes in volatility ($\widehat{Var}(\Delta A)$) into the contributions from each fundamental input:

1. The volatility of manufacturing employment growth ($Var(\Delta M)$)
2. The volatility of nonmanufacturing employment growth ($Var(\Delta N)$)
3. Manufacturing's share of total employment ($\bar{\gamma}$)
4. The correlation[4] between each sector's employment growth ($Cor(\Delta M, \Delta N)$)

The left panel of figure 3 shows employment growth rates for the manufacturing and nonmanufacturing sectors over our sample period, with the vertical dashed line corresponding to the start of the Great Moderation. This illustrates that the reduction in $Var(\Delta M)$, which fell from 19.1pp in the pre-GM period to 6.9pp in the post-GM period, was much larger than for $Var(\Delta N)$, which fell from 2.6pp to 1.9pp over the same time.[5]

The right panel plots the manufacturing share of total employment, which fell from an average of 23.5% pre-GM to 14.5% post-GM. Holding all else equal, equation 2 shows that lower values of $\bar{\gamma}$, which correspond to larger nonmanufacturing employment shares,

[3] Howes (2022) documents a strong relationship between changes in the manufacturing employment share and the growth rate of manufacturing employment during our sample period, which in theory could amplify the importance of these interaction terms in accounting for changes in total variance. However, because the variation in employment shares is tiny compared to variation in employment growth rates, the approximation errors within each sub-period turn out to be small in practice.

[4] While the covariance is what directly enters the approximation in equation 2, writing $Cov(\Delta M, \Delta N)$ as $\sqrt{Var(\Delta M)Var(\Delta N)}Cor(\Delta M, \Delta N)$ allows us to distinguish mechanical effects of changes in the volatility of each individual series from more fundamental changes in their comovement captured by their correlation.

[5] Table 10 in the appendix shows the detailed components of our approximation.

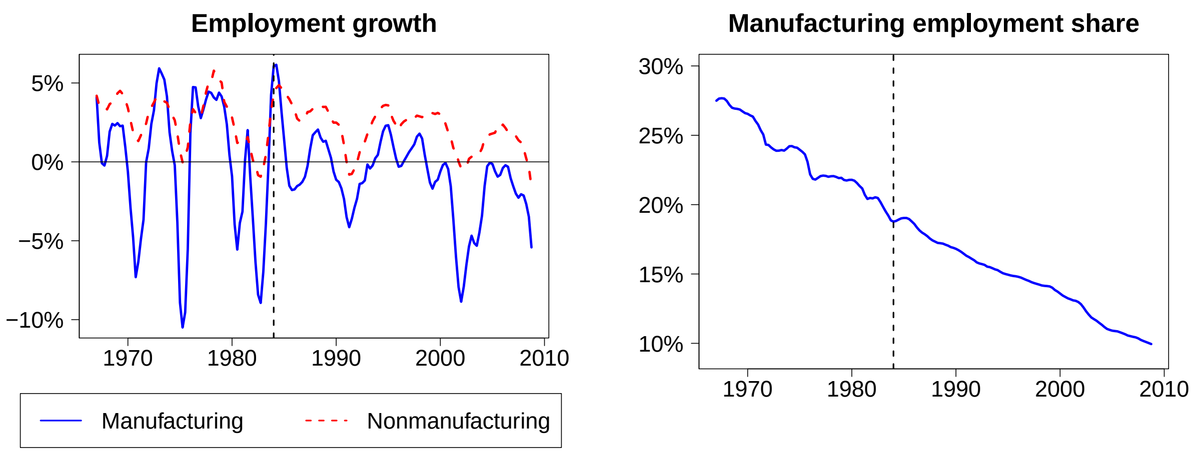


Figure 3: Employment growth rates and shares

*Notes:* The left panel plots the year-over-year quarterly growth rates for manufacturing (solid blue) and nonmanufacturing (dashed red) employment. The right panel plots the manufacturing share of total employment. The dashed vertical line corresponds to the first quarter of 1984, which is marked as the start of the Great Moderation in McConnell and Perez-Quiros (2000).

can also mechanically reduce the variance of total employment growth if $Var(\Delta N) < Var(\Delta M)$. Thus, to quantify the contributions of changes occurring entirely within the manufacturing sector, we need to distinguish the "fundamental changes" $\Delta F$—that is, those that would have taken place even if the sectoral composition of the economy had remained fixed—from the purely mechanical changes resulting from manufacturing's lower weight in total employment growth ("compositional volatility", $\Delta^C$). This exercise is analogous to a statistical agency calculating real GDP growth when both prices and quantities move simultaneously.

After obtaining the change in fundamental volatility $\Delta^F$, we further decompose it into its components: changes in volatility within each sector ($Var(\Delta M)$ and $Var(\Delta N)$) and the correlation between the two. Just as with real GDP, the contributions to the change in volatility coming from fundamentals, which we will define as $C^{VM}$, $C^{VN}$, and $C^{Cov}$, can be approximated by multiplying the change in each fundamental by it's "nominal" share of total volatility in the pre-GM period $\omega$:[6]

$$\Delta^F \approx C^{VM} + C^{VN} + C^{Cov} = \underbrace{\omega^M \left( \frac{Var^{new}(\Delta M)}{Var^{old}(\Delta M)} - 1 \right)}_{\text{Direct manufacturing contribution}} + \underbrace{\omega^N \left( \frac{Var^{new}(\Delta N)}{Var^{old}(\Delta N)} - 1 \right)}_{\text{Direct nonmanufacturing contribution}}$$
$$+ \underbrace{(1 - \omega^M - \omega^N) \left[ \left( \frac{Cor^{new}(\Delta M, \Delta N)}{Cor^{old}(\Delta M, \Delta N)} \right) \left( \sqrt{\frac{Var^{new}(\Delta M)}{Var^{old}(\Delta M)}} \right) \left( \sqrt{\frac{Var^{new}(\Delta N)}{Var^{old}(\Delta N)}} \right) - 1 \right]}_{\text{Covariance contribution}} \tag{3}$$

The exercise suggests that the total change in volatility due to the changing manufacturing share $\Delta^C$ led to a decline in employment volatility of about 11.3%. The contribution from changes in fundamental volatility $\Delta^F$ was much larger, leading do a decline of 45.2% in employment volatility. This fundamental decline can be accounted for with contributions of $C^{VM} = -14.1$pp, $C^{VN} = -8.1$pp, and $C^{Cov} = -23.0$pp. This suggests that, despite comprising less than one-quarter of total employment on average during the pre-GM period, the direct contributions of the manufacturing sector alone ($C^{VM}$) played a larger role in reducing aggregate employment growth volatility than the direct contributions from all other sectors combined ($C^{VN}$).

We can take this decomposition one step further to account for the fact that lower values of $C^{VM}$ and $C^{VN}$ will also mechanically reduce the covariance term $C^{Cov}$. And because the correlation between $\Delta M$ and $\Delta N$ was virtually unchanged across the pre-GM and post-GM periods, these changes will be the primary driver of the change in $C^{Cov}$. The sector-specific variance terms enter the covariance contribution nonlinearly, but we obtain an approximate linear decomposition by ignoring changes in the correlation term and allocating the total covariance contribution $C^{Cov} = -23.0$pp across the manufacturing and nonmanufacturing sectors in proportion to their growth rates.[7] The final decomposition

[6]These expressions are shown in the bottom panel of table 10. For the manufacturing sector, for example, this share will be $\omega^M = \frac{(\bar{\gamma})^2 Var(\Delta M)}{\widehat{Var}(\Delta A)} = \frac{(0.235)^2 \times 19.08}{4.75} = 0.22$.

[7]Since the decline in employment volatility was $\frac{63.7}{33.8} = 1.88$ times larger for the manufacturing sector, we

of fundamentals (that is, non-compositional changes), which is summarized in table 2, can be written:

$$\Delta^F \approx \underbrace{\underbrace{C^{VM}}_{\text{Direct effect}} + \underbrace{C^{Cov}_M}_{\text{Covariance effect}}}_{\text{Total manufacturing contribution}} + \underbrace{\underbrace{C^{VN}}_{\text{Direct effect}} + \underbrace{C^{Cov}_N}_{\text{Covariance effect}}}_{\text{Total nonmanufacturing contribution}} \tag{4}$$

This decomposition highlights two important facts about the post-1984 decline in employment volatility. The first is that $\Delta^F$ is much larger than $\Delta^C$, suggesting the Great Moderation resulted primarily from changes in the fundamental behavior of each sector, rather than mechanical composition effects due to a shrinking manufacturing sector. The second is that changes specific to the manufacturing sector ($-29.1$pp) accounted for roughly two thirds of the decline in total fundamental volatility ($-45.2\%$). These stylized facts motivate our quantitative exercises in section 4, in which we focus on the fundamental changes in volatility generated by easing financial constraints in our model while holding the relative size of each sector constant. In the next section, we apply the same decomposition to financial data.

## 2.3 Manufacturing and financial volatility

As discussed above, the reduction in employment volatility in the Great Moderation was accompanied by an increase in financial volatility, and the same decomposition from the previous section can be applied to financial data to understand the sources of this change. An ideal data set for this exercise would be a quarterly series of financial variables that covered our entire sample period for both the manufacturing and nonmanufacturing sectors. However, unlike measures of real activity, comprehensive measures of financial variables are much more difficult to obtain at the industry level in the US.[8]

can pin down each sector's contribution with the equations $\frac{C^{Cov}_M}{C^{Cov}_N} = 1.88$ and $C^{Cov} = -23.0 = C^{Cov}_M + C^{Cov}_N$.

[8] The Internal Revenue Service Statistics of Income data report aggregate income and balance sheet information by industry, but they are only available starting in the 1990s, and only at an annual frequency. The

Table 2: Total employment growth variance decomposition

| **Source** | **Contribution** |
|---|---|
| **Total changes from composition ($\Delta^C$)** | **–11.3%** |
| **Total changes from fundamentals** ($\Delta^F = C^{VM} + C^{VM} + C^{Cov}$) | **–45.2%** |
| **Direct manufacturing effect** ($C^{VM}$) | **–14.1** |
| **Direct nonmanufacturing effect** ($C^{VN}$) | **–8.1** |
| **Total covariance effect** ($C^{Cov}$) | **–23.0** |
| Approx. manufacturing covariance effect ($C_M^{Cov}$) | –15.0 |
| Approx. nonmanufacturing covariance effect ($C_N^{Cov}$) | –8.0 |
| Total manufacturing contribution ($C^{VM} + C_M^{Cov}$) | –29.1 |
| Total nonmanufacturing contribution ($C^{VN} + C_N^{Cov}$) | –16.1 |
| **Total change in employment growth volatility ($\Delta^T$)** | **–51.4%** |

*Notes:* This table shows the decomposition of changes in employment growth volatility during the Great Moderation from equations 3. The top row reports the total change in volatility due to changing manufacturing share ($\Delta^C$); the second row shows the contribution from changes in fundamental volatility ($\Delta^F$)—that is, changes in volatility unrelated to composition effects. Fundamental volatility can be broken down further into direct contributions from the manufacturing sector ($C^{VM}$), nonmanufacturing sector ($C^{VN}$), and covariance effects ($C^{Cov}$). The table also provides an approximate allocation of the covariance contribution across manufacturing and nonmanufacturing sectors. The bottom rows summarize the total manufacturing and nonmanufacturing contributions, highlighting that changes specific to the manufacturing sector (-29.1pp) accounted for roughly two-thirds of the decline in total fundamental volatility (-45.2%).

To construct distinct financial time series for the manufacturing and nonmanufacturing sectors, we combine data from the Federal Reserve's US Financial Accounts, the BEA's

US financial accounts provide a long time series of quarterly data, but do not contain information about specific industries. And while aggregate financial series can be constructed from firm-level Compustat data, these will omit smaller private firms.

National Income and Product Accounts (NIPA), and the Census Bureau's Quarterly Financial Report for Manufacturing Corporations (QFR).[9] The QFR data include detailed income and balance sheet information for the universe of US manufacturing firms, including small and nonpublic firms. By taking the US aggregate series from the financial accounts and subtracting the manufacturing series from the QFR, we can obtain a time series of financial outcomes for the nonmanufacturing sector. To analyze how the volatility of financial variables changed during the Great Moderation, we follow Jermann and Quadrini (2009) and analyze debt-to-income and dividend-to-income ratios. We construct our measures as follows:

- **Dividends:** We measure aggregate dividends using total nonfinancial domestic dividends paid from the NIPA. We use *gross* dividend payments to facilitate comparison with the QFR and to avoid large jumps in *net* dividend payments in 2004-05 related to a tax repatriation holiday. These numbers are only available from the BEA at an annual frequency, so we linearly interpolate a quarterly series. Manufacturing dividends are calculated by annualizing the dividends paid series in the QFR. Nonmanufacturing dividends are calculated as the difference between the two.

- **Debt:** Aggregate debt comes from the Financial Accounts series for loans and debt securities for nonfinancial corporate business. Manufacturing debt is calculated as the sum of short-term bank debt, long-term bank debt, and other long-term debt from the QFR.[10] Nonmanufacturing debt is calculated as the difference between the two.

- **Income:** Total, manufacturing, and nonmanufacturing income data come from the BEA's national income statistics. We use total industry income because other potential measures, like value added or gross output, are not available at a quarterly

[9] See Howes (2023) for more details about the construction of consistent QFR time series.

[10] Other types of short-term debt are not recorded consistently over time due to methodological changes in the QFR, so we omit them from our analysis.

frequency for the earlier part of our sample. We choose to scale dividends by income rather than equity for two reasons. First, it standardizes the comparison with the debt-income ratio. Second, we do not have consistent measures of equity values for all firms by industry (the QFR data use book value, while the financial accounts use market value, preventing direct comparison).

We define $D_t^i$ for sector $i \in \{M, N\}$ at time $t$ as the ratio of debt ($Debt_t^i$) to income ($Y_t^i$), where variables without superscripts indicate aggregates:

$$D_t = \frac{Debt_t}{Y_t} = \frac{Debt_t^M + Debt_t^N}{Y_t^M + Y_t^N} = D_t^M \left(\frac{Y_t^M}{Y_t}\right) + D_t^N \left(\frac{Y_t^N}{Y_t}\right) \equiv \gamma D_t^M + (1-\gamma) D_t^N \quad (5)$$

The dividend-income ratio is defined analogously. This formula is similar to the one derived in the previous section. However, instead of expressing total income growth as an average of growth rates in each sector weighted by lagged employment, this expresses total financial ratios as an average of the ratios in each sector weighted by that sector's share of total income $\gamma$. This allows for the same type of variance decomposition in the previous section:

$$Var(D) \approx (\bar{\gamma})^2 Var(D^M) + (1-\bar{\gamma})^2 Var(D^N) + 2\bar{\gamma}(1-\bar{\gamma}) Cov(D^M, D^N) \quad (6)$$

An illustration of each component of this decomposition is shown in figure 4. The top panels show that the volatility of the debt-income and dividend-income ratios increased for both manufacturers and nonmanufacturers, but that the increase was much larger for the former. The bottom panel shows the manufacturing share of income, which displays a similar trend over the last several decades to that of the employment share shown in figure 3.

The contributions of each sector to this change in aggregate volatility for the debt-income and dividend-income ratios are shown in table 3. This table highlights three important stylized facts about changes in firm balance sheet volatility during the Great

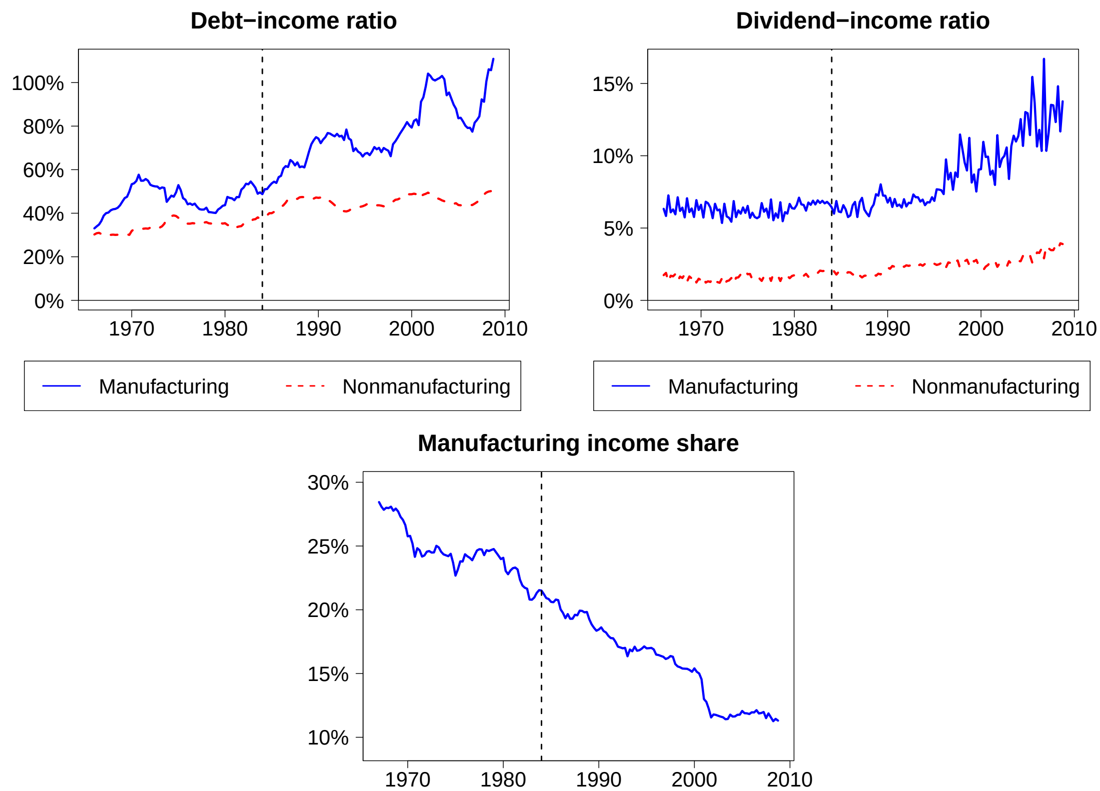


Figure 4: Financial ratios and sector income shares

*Notes:* The top panels plot the ratios of debt and dividend payments to income for the manufacturing (solid blue) and nonmanufacturing (dashed red) sectors. The bottom panel plots manufacturing's share of total income. The dashed vertical line corresponds to the first quarter of 1984, which is marked as the start of the Great Moderation in McConnell and Perez-Quiros (2000).

Moderation. First, as with employment, the negative values for $\Delta^C$ show that the shrinking of the manufacturing sector contributed to a reduction in volatility. Second, with employment, the fundamental changes within each sector $\Delta^F$ resulted in large increases in volatility. And third, despite comprising a small share of total income, we find that the direct contributions of the manufacturing sector ($C^{VM}$) were far larger than those of the nonmanufacturing sector ($C^{VN}$), accounting for 53% and 44% of the total change in volatility for the aggregate debt-income and dividend-income ratios, respectively.

As with the employment share, these direct effects paint an incomplete picture of each sector's contribution to the total change. However, unlike with employment growth, the covariance contributions $C^{Cov}$ cannot easily be decomposed into their sector-specific

Table 3: Financial ratio variance decomposition

| Source | Debt-income | Dividend-income |
|---|---|---|
| $\Delta^C$ | **–33.3%** | **–31.5%** |
| $\Delta^F = C^{VM} + C^{VM} + C^{Cov}$ | **+365.0%** | **+1,918.3%** |
| $C^{VM}$ | +194.3 | +848.0 |
| $C^{VN}$ | +16.1 | +291.5 |
| $C^{Cov}$ | +154.6 | +778.9 |
| $\Delta^T$ | **+210.3%** | **+1,282.8** |

*Notes*: This table presents the decomposition of changes in financial ratio volatility during the Great Moderation for both debt-income and dividend-income ratios. The first row ($\Delta^C$) shows the change in volatility due to compositional effects;. the second row ($\Delta^F$) displays the total change in fundamental volatility, which increased substantially for both ratios. This increase is further broken down into direct contributions from the manufacturing sector ($C^{VM}$), nonmanufacturing sector ($C^{VN}$), and covariance effects ($C^{Cov}$). The manufacturing sector accounted for 3 times more of the decline in dividend volatility than the nonmanufacturing sector and 12 times more for the decline in debt volatility.

components because of the substantial approximation errors induced by large changes in correlations between the ratios in each sector before and after the onset of the Great Moderation. Nonetheless, the direct contributions alone are sufficiently large to highlight the importance of the manufacturing sector in driving changes in financial volatility even without accounting for these spillovers.[11]

Having established that manufacturing was the primary driver of changes in both real and financial volatility during the Great Moderation, we next provide evidence that easing financial constraints can parsimoniously generate both patterns.

[11]Focusing on the direct effect also puts the empirical results on more equal footing with our model in section 4, which does not generate any meaningful change in cross-sector correlations of financial variables.

# 3 Evidence from interstate banking deregulation

The stylized facts presented in the previous section established that the Great Moderation led to changes in both real and financial volatility that were disproportionately driven by the manufacturing sector. In this section, we provide causal empirical evidence that changes in the financial sector were an important driver of these effects—and show that they operated disproportionately through manufacturing—using a well-studied natural experiment: the staggered implementation of US interstate bank deregulation (IBD).

Prior to the late 1970s, banks in the U.S. operated locally. Banks were not permitted to open branches outside of the state in which they were headquartered, and many states had additional regulations preventing branches from opening in new cities. This began to change in 1978, and throughout the 1980s and early 1990s, almost every US state passed IBD legislation. Jayaratne and Strahan (1996) first showed that this deregulation led to an expansion in economic activity, and subsequent studies including Morgan et al. (2004) and Acharya, Imbs, and Sturgess (2011) showed that IBD also led to reductions in state-level nonfinancial volatility.[12] We complement this work by studying how the size of a state's manufacturing sector affected its response to IBD. Specifically, we estimate the following equation:

$$Y_t^i = \alpha^i + \delta_t + \theta IBD_t^i + \beta \left( IBD_t^i \times share^i \right) + \epsilon_t^i, \tag{7}$$

where each observation $Y_t^i$ corresponds to outcome $Y$ in state $i$ at year $t$; $\alpha^i$ and $\delta_t$ represent state and year fixed effects, respectively; and $IBD_t^i$ is a deregulation indicator that takes on values of zero prior to interstate banking deregulation and one after. Relative to past work, the new feature of this specification is the interaction term $(IBD_t^i \times share^i)$, where $share^i$ captures the importance of the investment-producing sector in state $i$. For

[12] Recent work by Herrera, Minetti, and Schaffer (2024) also shows that credit reallocation increased for public firms after states implement IBD. This aligns closely with our findings in section 2.3, although the lack of comprehensive financial data at the state-by-sector level prevent us from studying financial volatility using this framework.

our baseline measure of the size of the investment-producing sector, we fix each state's manufacturing employment share at its 1977 level, which was the last year for which no state had passed IBD legislation.

The deregulation dates are taken from Strahan et al. (2003); they begin with Maine in 1978 and conclude with the nationwide deregulation of IBD in 1994. We follow the IBD literature and exclude South Dakota and Delaware given their unique position in the development of the credit card industry. We also follow Morgan et al. (2004) and exclude Alaska, North Dakota, and South Dakota as outliers in our baseline specification, though this is not crucial for the main results. The deregulation dates for each state are shown in appendix A.[13]

The outcome variables we consider are the volatility of employment, gross state product (GSP), and the unemployment rate at the state level. To calculate these volatility measures, we first decompose the logs of these series ($X_t^i$) into their secular and cyclical components $X_t^i = trend_t^i + cycle_t^i$, using Hamilton's (2018) filter. The outcome variable of interest is then calculated as $Y_t^i = |cycle_t^i|$. This is similar in spirit to the approach of Morgan et al. (2004), who use the absolute value of the deviations obtained from regressing growth rates on state and year fixed effects as their baseline measure of volatility. Summary statistics for these measures are shown in table 4. Real GSP and employment are in log points ($\times 100$), while the unemployment rate is in percentage points.

Because the units of these deviations are in logs, interpreting the coefficients of this regression is straightforward. In the case of GSP, for example, an additional 1 percentage-point higher manufacturing employment share in state $i$ means that, following the implementation of IBD legislation, the expected cyclical component in that state's GSP (measured as a percent of total GSP) would be an additional $\beta$pp larger on average in the post-implementation period relative to untreated states. If $\beta < 0$, then states with larger

[13] Recent work including Mian, Sufi, and Verner (2020) and Howes (2022) has shown that implementation of IBD affected the subsequent composition of a state's employment, but both show that the pre-existing differences in these compositions did not predict a state's decision to deregulate.

manufacturing sectors experience larger reductions in the size of their cyclical deviations following IBD. The results are shown in table 5 with the outcome for each column labeled at the top. The bottom row corresponds to $\beta$ in equation 7.

This suggests that an additional one percentage point increase in a state's 1977 manufacturing employment share would have led to an additional reduction in the average magnitude of that state's cyclical GSP deviations by 0.12pp following IBD. This increase is both statistically and economically significant; based on the values shown in table 4, this specification would predict that a one standard deviation increase in a states' manufacturing employment share (4.88pp) reduces the magnitude of that state's average cyclical GSP deviation (measured as a share of GSP) by 0.60pp. This represents more than 25% of the standard deviation across the entire sample, and almost 40% of the difference between the pre- and post-1984 periods shown in the bottom row of table 4.

The second and third columns show the estimated effects for employment and unemployment fluctuations. A one standard deviation increase in the manufacturing employment share leads to an additional reduction in the average size of a state's employment and unemployment rate fluctuations of about 0.14pp and 0.12pp, respectively. These values represent roughly 12% of the total post-1984 change for employment and 14% of the change for the unemployment rate. These results are consistent with the findings of Owyang, Piger, and Wall (2008), who analyze the Great Moderation at the state level and find larger reductions in volatility for states with higher levels of durable goods production. Our findings also complement those of Kundu and Vats (2020) in showing that banking deregulation contributed to the Great Moderation; however, while they study how financial deepening can smooth shocks across sates, we instead focus on its disproportionate role across sectors.

To summarize, this section showed that the plausibly exogenous variation in improved credit access following IBD led to larger reductions in real activity for states with larger manufacturing sectors. The goal of this exercise is not to show that IBD was the

Table 4: State-level cyclical fluctuations

| | $share^i$ (pp) | RGSP (%) | Employment (%) | UR (pp) |
|---|---|---|---|---|
| | Entire sample (1973-2008) | | | |
| 5th percentile | 2.69 | 0.28 | 0.18 | 0.08 |
| 25th percentile | 6.81 | 1.33 | 0.89 | 0.38 |
| Mean | 9.93 | 3.16 | 2.17 | 0.99 |
| Median | 9.60 | 2.69 | 1.79 | 0.80 |
| Standard deviation | 4.88 | 2.37 | 1.73 | 0.84 |
| 75th percentile | 12.08 | 4.49 | 3.00 | 1.35 |
| 95th percentile | 19.28 | 7.46 | 5.56 | 2.63 |
| | | Pre-1984 | | |
| 5th percentile | | 0.78 | 0.39 | 0.13 |
| 25th percentile | | 2.68 | 1.51 | 0.79 |
| Mean | | 4.40 | 3.03 | 1.74 |
| Median | | 4.19 | 2.69 | 1.58 |
| Standard deviation | | 2.50 | 2.02 | 1.22 |
| 75th percentile | | 5.75 | 4.08 | 2.43 |
| 95th percentile | | 8.06 | 6.71 | 3.98 |
| | | Post-1984 | | |
| 5th percentile | | 0.24 | 0.14 | 0.08 |
| 25th percentile | | 1.16 | 0.75 | 0.34 |
| Mean | | 2.96 | 1.80 | 0.80 |
| Median | | 2.45 | 1.47 | 0.71 |
| Standard deviation | | 2.29 | 1.43 | 0.57 |
| 75th percentile | | 4.26 | 2.44 | 1.13 |
| 95th percentile | | 7.08 | 4.58 | 1.81 |
| | | Change in mean from pre-1984 to post-1984 (pp) | | |
| | | -1.44 | -1.23 | -0.78 |

*Notes:* This table shows summary statistics for the IBD estimates from section 3 for log real gross state product (RGSP), log total employment, and the unemployment rate (UR). Summary statistics omit the states dropped in the main analysis: DE, SD, AK, ND, and WY. The top panel shows statistics across the entire sample (1973-2008). The middle panel shows statistics calculated from 1973-1983. The bottom panel shows statistics from 1984-2008. $share^i$ is the durable goods manufacturing employment share in 1977 and is measured in percentage points. Because this share is fixed for all time periods, it is only shown in the "Entire sample" section. RGSP, employment, the unemployment rate, and compensation are all measured as the absolute value of the cyclical component obtained from using the Hamilton (2018) filter. RGSP and employment are measured in log points ($\times 100$) and the unemployment rate is measured in percentage points. The bottom row shows the average deviation in the post-1984 series minus the average deviation in the pre-1984 series.

only, or even the primary, change in financial markets that occurred during the early 1980s; important regulatory and technological developments during this period also in-

Table 5: Effects of employment shares on IBD transmission

| | RGSP | Employment | Unemployment rate |
|---|---|---|---|
| $IBD_t^i$ | 0.0132*** | 0.000426 | 0.000928 |
| | (0.00479) | (0.00318) | (0.00114) |
| $IBD_t^i \times share^i$ | -0.124*** | -0.0289** | -0.0249*** |
| | (0.0276) | (0.0131) | (0.00748) |
| $N$ | 1334 | 1656 | 1440 |

Standard errors clustered by state in parentheses: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* This table shows the results of estimating Equation 7. $IBD_t^i$ is a dummy variable taking values of zero prior to a state implementing interstate banking deregulation and one after. $share^i$ is the fraction of state $i$'s total employment in the manufacturing sector in 1977. The dependent variable is the absolute value of the cyclical deviation of each series calculated using the Hamilton (2018) filter. GSP and employment are in logs before filtering, while the unemployment rate is in levels. We follow Morgan et al. (2004) and exclude DE and SD given their unique role in the credit card industry, and AK, ND, and WY as outliers. Regressions include data from 1973-2008.

cluded syndicated loans, junk bonds, securitization, elimination of interest caps under Regulation Q, among many others.[14] Rather, the purpose of this section is to provide more targeted causal evidence for the idea that financial deepening can generate the patterns documented in section 2. It is this broader concept of financial deepening, rather than IBD specifically, that we intend to capture with our model exercise in the next section.

# 4 Model

This section develops a model that can replicate the stylized facts documented in section 2 via the causal mechanisms studied in section 3. The financial frictions in our model follow the framework developed in Jermann and Quadrini (2009) and (2012). In section 4.1, we begin by illustrating the link between financial and real activity generated by this mechanism in a simplified, single-sector version of the model. The simple model illustrates how financial frictions enter the model while abstracting from more complicated sectoral

[14] See Frame and White (2004) for a thorough review of empirical work studying financial innovation.

interactions. Next, in section 4.2, we integrate these frictions into a medium-scale New Keynesian model with distinct manufacturing and nonmanufacturing sectors in which manufactured goods are more important inputs into investment production. Finally, in section 4.3, we argue that easing financial constraints in the model can generate the stylized facts of the Great Moderation for both real and financial activity.

## 4.1 Financial frictions

In each period firms produce output $y_t$ using capital $k_t$ and labor $n_t$. In addition to choosing how much labor to hire, firms optimally choose investment $x_t$ and long-term debt $b_t$, and pay out profits as dividends $d_t$ according to the following budget constraint:

$$y_t - w_t n_t - x_t + \frac{b_t}{R_t} = b_{t+1} + \varphi(d_t) \tag{8}$$

We assume that interest payments on debt are tax deductible in order to generate a meaningful tradeoff between debt and equity financing. For a given tax benefit $\tau$ and a nominal risk-free rate $i_t$, the effective nominal interest rate paid by firms will be $R_t = (1-\tau)i_t + 1$. Firms also face frictions that distort the substitution between debt and equity, which can reflect pecuniary costs of equity issuance or share repurchases as well as a managerial desire to smooth dividend payments. A firm seeking to pay out a given level of dividends $d_t$ will incur a total cost of $\varphi(d_t)$, which includes includes the dividend disbursement itself plus an additional quadratic cost when its dividend payouts differ from their steady-state level $\bar{d}$:

$$\varphi(d_t) = d_t + \kappa \left(d_t - \bar{d}\right)^2. \tag{9}$$

Firms must also borrow $\ell_t$ intratemporally (at zero net interest) to fund their current period expenditures. Firms make the decision to default after revenues are realized but before they have repaid the intraperiod loan, at which point the total liabilities are $\ell_t + \frac{b_t}{R_t}$. Because the firm can divert the proceeds from production in the event of default, the lender will only be able to recover the value of the capital stock net of the intertemporal debt obligations with some probability $\zeta_t$. This leads to a borrowing constraint:

$$\ell_t = w_t n_t + x_t + d_t + b_{t-1} - \frac{b_t}{R_t} \leq \zeta_t \left( k_{t+1} - \frac{b_t}{R_t} \right). \tag{10}$$

By combining these equations, we can express the firm's problem recursively:

$$V(\mathbf{s}; k, b) = \max_{d,n,k',b'} \left\{ d + \mathbb{E}\left[ m' V(\mathbf{s}'; k', b') \right] \right\}, \tag{11}$$

where primed variables denote next-period values. Here $\mathbf{s}$ represents a vector of exogenous state variables, $m$ represents the firm's stochastic discount factor taking into account the equity adjustment costs, and $\mathbb{E}$ is the rational-expectations operator conditional on current information. This profit maximization problem is subject to the following constraints:

$$(1-\delta)k + F(\mathbf{s}, k, n) - wn + \frac{b'}{R} = b + \varphi(d) + k', \tag{12}$$

$$\zeta \left( k' - \frac{b'}{1+i} \right) = F(\mathbf{s}, k, n) = y, \tag{13}$$

where we have substituted out for output and investment using the production function and a standard law of motion for capital $k' = (1-\delta)k + x$, where $\delta$ is the depreciation rate.

Let $\lambda$ and $\mu$ be the Lagrange multipliers on firms' budget (12) and collateral constraints (13), respectively, with the latter assumed to be binding in equilibrium. First-order conditions for dividends ($d$), labor ($n$), next period's capital ($k'$), and intertemporal debt ($b'$) are

$$1 - \lambda \varphi_d(d) = 0, \tag{14}$$

$$\lambda F_n - \lambda w - \mu F_n = 0, \tag{15}$$

$$\mathbb{E} m' V_k' - \lambda + \mu\zeta = 0, \tag{16}$$

$$\mathbb{E} m' V_b' + \frac{\lambda}{R} - \frac{\mu\zeta}{1+i} = 0, \tag{17}$$

where subscripts on functions denote partial derivatives with respect to the subscripted variables.

The two envelope conditions for the two endogenous state variables, long-term debt and capital are

$$V_k = \lambda \left[1 - \delta + F_k\right] - \mu F_k, \tag{18}$$

$$V_b = -\lambda. \tag{19}$$

The first-order and envelope conditions can be combined to yield the following equilibrium conditions:

$$F_n = w \left( \frac{1}{1 - \mu \varphi_d(d)} \right), \tag{20}$$

$$\mathbb{E} m' \left( \frac{\varphi_d(d)}{\varphi_d(d')} \right) \left[1 - \delta + (1 - \mu' \varphi_d(d')) F_k(z', k', n')\right] + \zeta \mu \varphi_d(d) = 1, \tag{21}$$

$$R \mathbb{E} \left[ m' \left( \frac{\varphi_d(d)}{\varphi_d(d')} \right) \right] + \zeta \mu \varphi_d(d) \left( \frac{R}{1+i} \right) = 1. \tag{22}$$

These equations highlight the link between financial and real activity in the model. Equation 20 shows that a tighter financial constraint—captured by a higher value of the Lagrange multiplier $\mu$—will lead to a larger wedge between wages and the marginal product of labor. Similarly, equation 22 shows that expecting to pay higher dividend adjustment costs in the future ($\mathbb{E}\left[\varphi_d(d')\right]$) can distort borrowing decisions today through the same channels as expected fluctuations in the standard stochastic discount factor.

## 4.2 Full model

This section integrates the financial frictions described in Section 4.1 into a multi-sector medium-scale New Keynesian model with both real and nominal frictions. In it, manufactured and non-manufactured output are both used to produce consumption and investment goods; the key distinction is that manufactured inputs play a larger role in the production of investment goods, while non-manufactured inputs play a larger role in the production of consumption goods.

After presenting the model, we use it to evaluate the ability of changing financial constraints to explain the changes in volatility that followed the Great Moderation.

### 4.2.1 Households

Households get utility from consuming output from both the manufacturing ($M$) and non-manufacturing ($N$) sectors and disutility from supplying labor in each sector. They receive nominal wages, dividend payments from firms, transfer payments from the government, and interest income from nominal bond holdings.[15] The representative household's problem is

$$\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[ \log(C_t) - \alpha \frac{N_t^{1+\gamma}}{1+\gamma} \right], \tag{23}$$

$$\text{subject to} \qquad P_t C_t + \frac{B_{t+1}}{(1+i_t)} = B_t + W_t^N N_t^N + W_t^M N_t^M + P_t \varphi(d_t) + P_t T_t, \tag{24}$$

where superscripts $N$ and $M$ denote non-manufacturing and manufacturing, respectively, $C_t$ and $N_t$ are consumption and labor aggregates, $B_t$ denotes maturing nominal bonds, $i_t$ is the nominal interest rate, $N_t^i$ and $W_t^i$ are labor hours and nominal wages in each sector, real dividend payments $\varphi(d_t)$ are gross of adjustment costs, $T_t$ is real transfers, and $P_t$ is

[15] Markets are complete, so households also trade in a full set of contingent claims, which are suppressed in equation 24.

the consumption price index. Consumption and labor aggregates are given by

$$C_t = \left(C_t^N\right)^{\eta^C} \left(C_t^M\right)^{1-\eta^C}, \tag{25}$$

$$N_t = \left[\chi^{\frac{-1}{\eta}} \left(N_t^N\right)^{\frac{1+\eta}{\eta}} + (1-\chi)^{\frac{-1}{\eta}} \left(N_t^M\right)^{\frac{1+\eta}{\eta}}\right]^{\frac{\eta}{1+\eta}}. \tag{26}$$

This consumption aggregator implies that the price index for consumption is

$$P_t = \left(\frac{P_t^N}{\eta^C}\right)^{\eta^C} \left(\frac{P_t^M}{1-\eta^C}\right)^{1-\eta^C}, \tag{27}$$

where $P_t^i$ is the nominal price of consumption from sector $i$. With these weights, the consumption price index implies that $\sum_i P_t^i C_t^i = P_t C_t$. In equilibrium, $\eta^C$ will represent the household consumption expenditure share on nonmanufactured goods, so that $p_t^N C_t^N = \eta^C C_t$ and $p_t^M C_t^M = (1-\eta^C) C_t$, where lowercase $p^i \equiv \frac{P^i}{P}$ denotes the relative price of sector $i$'s good to the aggregate consumption good. Gross inflation is then $\pi_t \equiv \frac{P_t}{P_{t-1}}$.

Equation 26 shows that, rather than being perfectly substitutable across sectors, households' disutility of labor is a composite of labor in the manufacturing and nonmanufacturing sectors as in Horvath (2000). This setup maintains tractability while allowing for differences in the equilibrium real wages across sectors. Households earn the risk-free interest rate $(1+i_t)$ on their nominal bond holdings, which are used to fund firms' borrowing, and receive dividends $d_t$ and net lump sum transfers (used to fund firms' interest subsidies) $T_t$[16]. The Lagrange multiplier on the budget constraint, which is used to discount dividend payments from firms, is $\lambda_t$. In this framework, the stochastic discount factor $m$ for real payments can be expressed as $m_t = \beta \mathbb{E}_t \left[\frac{\lambda_{t+1}}{\lambda_t}\right]$. Household optimality conditions for consumption, labor supply, and nominal bond holdings are:

[16] In equilibrium, $T_t = -\left(\frac{B_{t+1}}{(1+(i_t-1)(1-\tau))} - \frac{B_{t+1}}{i_t}\right)$.

$$\frac{1}{C_t} = \lambda_t, \tag{28}$$

$$\lambda_t w_t^i = \alpha \left(\chi^i\right)^{\frac{-1}{\eta}} (N_t)^{\gamma - \frac{1}{\eta}} \left(N_t^i\right)^{\frac{1}{\eta}}, \tag{29}$$

$$1 = \mathbb{E}_t \left[ m_t \frac{1+i_t}{\pi_{t+1}} \right], \tag{30}$$

where $\chi^N = \chi$, $\chi^M = (1-\chi)$, and aggregate labor $N_t$ is defined in Equation 26.

### 4.2.2 Firms

The economy consists of manufacturing ($M$) and nonmanufacturing ($N$) firms. Within each sector $i \in \{M, N\}$, a representative firm produces according to a Cobb-Douglas production technology that includes labor $N_t^i$, capital $K_t^i$, and both manufactured and nonmanufactured intermediate inputs $MM_t^i$ and $MN_t^i$, with aggregate and sector-specific productivity terms $A_t$ and $X_t^i$:

$$Y_t^i = A_t X_t^i \left(MN_t^i\right)^{\nu^N} \left(MM_t^i\right)^{\nu^M} \left(K_t^i\right)^{\theta} \left(N_t^i\right)^{1-\theta-\nu^N-\nu^M}. \tag{31}$$

While labor can be perfectly substituted as inputs across sectors, capital is sector specific, and output in each sector is unique and separately priced. Total investment in each sector $I_t^i$ is also a composite of both manufactured $(IM_t^i)$ and nonmanufactured $(IN_t^i)$ intermediate inputs:

$$I_t^i = \left(IM_t^i\right)^{\psi} \left(IN_t^i\right)^{1-\psi}. \tag{32}$$

The relative price of one unit of composite investment is $p_t^I = \left(\frac{p_t^M}{\psi}\right)^{\psi} \left(\frac{p_t^N}{1-\psi}\right)^{1-\psi}$. In addition, investment is subject to investment-specific technology (IST) shocks for each sector $v_t^i$, as well as adjustment costs that penalize quadratic deviations of investment from its prior level. Together, these imply the following law of motion for capital:

$$K^i_{t+1} = (1-\delta)K^i_t + \exp(v^i_t)\left[1 - \frac{\omega}{2}\left(\frac{I^i_t}{I^i_{t-1}} - 1\right)^2\right] I^i_t. \tag{33}$$

In each sector, a continuum of firms produce differentiated goods that are combined into final manufactured and nonmanufactured goods by a perfectly competitive intermediary according to a standard Dixit-Stiglitz aggregator with elasticity of substitution $\epsilon$. Letting $p^i_j$ denote the price of firm $j$ in sector $i$, then demand from the final goods producer in sector $i$ for firm $j$'s output is $Y^i_j = \left(\frac{p^i_j}{p^i}\right)^{-\epsilon} Y^i$.

Nominal prices in each sector are also subject to quadratic adjustment costs with sector-specific parameters $\phi^i$. This leads to the following sector-specific pricing optimality conditions, with $mc^i_t$ representing each sector's marginal cost:

$$\left((1-\epsilon)p^i_t + (\epsilon)mc^i_t\right) - \phi^i\left(\pi^i_t - 1\right)\pi^i_t + \phi^i\mathbb{E}_t\left[M_{t+1}\left(\frac{\varphi_{d,t}}{\varphi_{d,t+1}}\right)\left(\pi^i_{t+1} - 1\right)\pi^i_{t+1}\left(\frac{Y^i_{t+1}}{Y^i_t}\right)\right] = 0. \tag{34}$$

In addition to these pricing adjustment costs, firms in each sector face financial constraints as described in the previous section. The equations describing these frictions in our setting are below:

$$\zeta_t\mathbb{E}_t\left(p^I_t K^i_{t+1} - \frac{B^i_{t+1}}{(1+i_t)}\right) = p^i_t Y^i_t, \tag{35}$$

$$p^i_t Y^i_t - p^I_t I^i_t - p^M_t MD^i_t - p^N_t MN^i_t - w_t N^i_t + \frac{B^i_{t+1}}{R_t} = B^i_t + \varphi(d^i_t). \tag{36}$$

The dividend adjustment cost $\varphi(d^i_t)$ takes the same functional form as shown in equation 9. We assume that all firms face the same aggregate debt constraint parameter $\zeta_t$, but allow for the equity adjustment costs $\kappa^i$ and steady state dividend payouts $\bar{d}^i$ to potentially vary across sectors. As in Jermann and Quadrini (2012), we assume that the decision to default is made after revenues are realized and capital depreciates, but before the intratemporal debt is repaid. This implies that the enforcement constraint (equation 35) will value the capital stock at current prices.

#### 4.2.3 Equilibrium and Solution

Market clearing implies that total gross output in each sector will be equal to the sum of that sector's inputs to consumption, investment, and intermediate material goods:

$$Y_t^M = \sum_i \left( IM_t^i + MM_t^i \right) + C_t^M \qquad \text{and} \qquad Y_t^N = \sum_i \left( IN_t^i + MN_t^i \right) + C_t^N \tag{37}$$

Finally, to close the model, we specify a standard Taylor Rule:

$$\beta(i + i_t) = (\beta(1 + i_{t-1}))^{\rho} \left( \pi_t^{\phi_\pi} \right)^{1-\rho} \exp(e_t^M). \tag{38}$$

Following Monacelli (2009), we ensure that the calibration results in the constraint binding in the steady state and then linearize around that steady state, assuming that it will continue to bind for small perturbations. Appendix D derives the full set of first-order and equilibrium conditions. The model's parameter values, which are shown in the appendix table 11, are primarily taken from Jermann and Quadrini (2012) and Howes (2023).

### 4.3 Financial Constraints and Volatility

In order to study within the model the financial deepening we identify as an important driver of the Great Moderation, we simulate the model for two parameterizations: one in which the dividend adjustment cost parameters $\kappa^i$ are large, and one in which they are small.[17] All other aspects of the calibration—most importantly the variances of all shocks—are identical across the two model simulations.

Table 6 displays the changes in variance of key macro and financial variables in the

[17] Following Jermann and Quadrini (2012), set $\kappa^i = 0.146$ in each sector in the pre-Great Moderation calibration. We set $\kappa^i = 0.01$ in the post-Great Moderation calibration.

Table 6: Model variances with and without financial frictions.

| Model Variable | Change in variance (percent) |
|---|---|
| Output | -40.7 |
| Employment | -42.8 |
| Debt | 20.3 |
| Dividends | 119.2 |

model. As in our results above, the variance of output and employment falls in the post-Great Moderation period, while that of financial variables rises substantially. The vast majority of the overall changes in these second moments is accounted for by changes in the model's response to financial shocks.[18] Model impulse responses to a financial shock are displayed in figure 5. When financial frictions are high, adjustment costs prevent firms from optimally changing the composition of their balance sheets, so they instead are forced to adjust output and employment; when those frictions are reduced, the response to financial shocks shifts from real variables to financial ones instead.

We can also perform the same decomposition of variances as in sections 2.2 and 2.3 using model simulated data instead of real data. We simply interpret the model simulation with high frictions as capturing the pre-Great Moderation period, and the the one with low frictions as the post-Great Moderation period. Table 7 compares the empirical and model-based decomposition for employment, and table 8 does the same for financial ratios.

Reducing financial frictions in the model results in a decline of employment volatility of 44%, almost identical to the 45.2% decline in fundamental volatility seen in the data.[19] In the decomposition of that change, manufacturing accounts for 83% of the decline in employment volatility in the model, somewhat larger than the 64% in the data. Moreover, the breakdown of the direct and covariance effects are also comparable.

The change in the volatility of financial variables is qualitatively similar to what we

[18]Recall that financial shocks in the model are captured by shocks to $\zeta_t$ the fraction of collateral recoverable by lenders after default.

[19]In the model decomposition, the total change is equal to the fundamental change; sector sizes are the same whether financial frictions are high or low, so there is no composition effect.

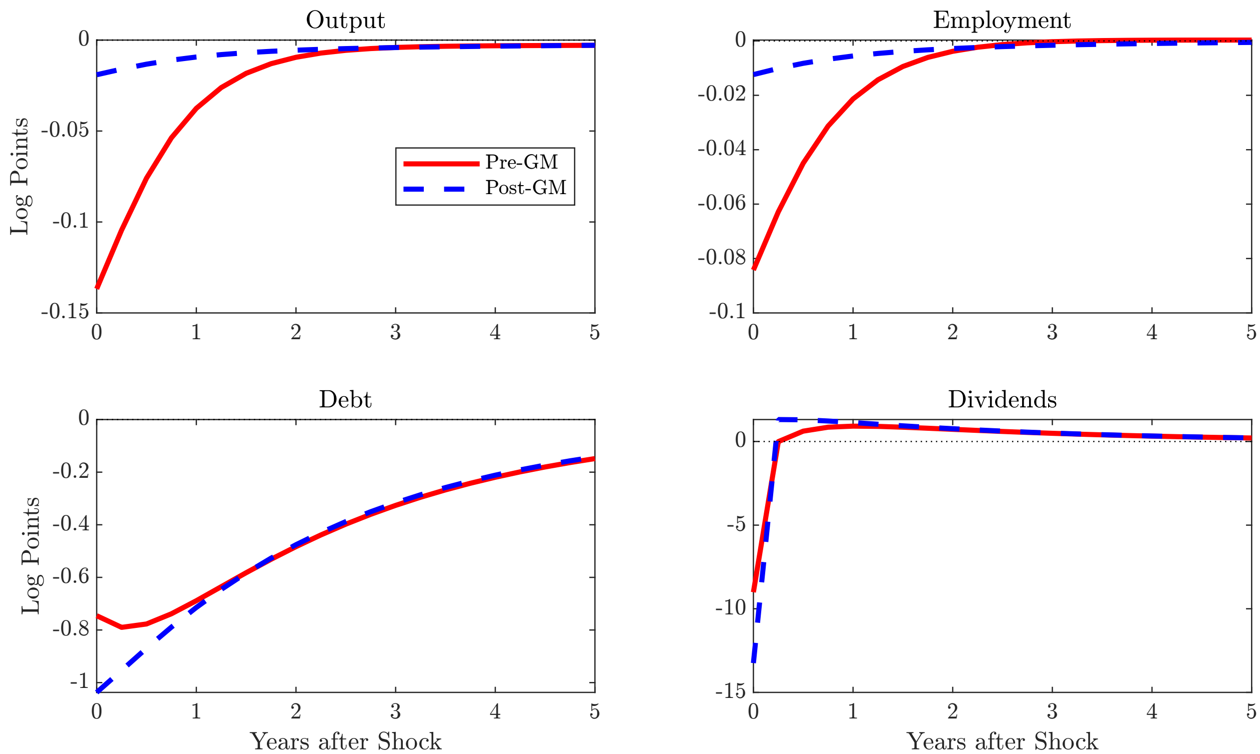


Figure 5: Impulse responses to a contractionary financial shock.

*Notes:* Pre-Great Moderation (red solid) has $\kappa = 0.146$ for each sector; post-Great Moderation (blue dashed) has $\kappa = 0.01$ for each sector.

see in the data, but the overall changes are an order of magnitude smaller. This mismatch is perhaps not surprising: the class of models that include these types of financial frictions are designed and calibrated to study the effect of these frictions on macroeconomic variables, not the dynamics of financial measures *per se*.[20] The magnitude of the variance changes notwithstanding, the model decomposition nevertheless yields a similar qualitative result to its empirical counterpart: the manufacturing sector accounts for a much larger share of the increase in financial volatility (about 2/3 for both debt and dividends) than the nonmanufacturing sector.

We can also pin down an important mechanism through which the reduction in financial frictions for the manufacturing share in particular accounts for these changes. Recall that in the model, physical investment is produced with a larger share of manu-

[20] Integrating a richer financial sector that can match the magnitude of the increase in financial volatility is likely a fruitful area for furture research.

Table 7: Total employment growth variance decomposition, data and model

| Source | Data **Employment** | Model ***Employment*** |
|---|---|---|
| **Total changes from composition ($\Delta^C$)** | **–11.3%** | **–** |
| **Total changes from fundamentals** ($\Delta^F = C^{VM} + C^{VM} + C^{Cov}$) | **–45.2%** | ***–44.0%*** |
| **Direct manufacturing effect** ($C^{VM}$) | **–14.1** | ***–22.9*** |
| **Direct nonmanufacturing effect** ($C^{VN}$) | **–8.1** | ***–5.3*** |
| **Total covariance effect** ($C^{Cov}$) | **–23.0** | ***–20.6*** |
| Approx manufacturing covariance effect ($C_M^{Cov}$) | –15.0 | *–13.7* |
| Approx nonmanufacturing covariance effect ($C_N^{Cov}$) | –8.0 | *–6.9* |
| Total manufacturing contribution ($C^{VM} + C_M^{Cov}$) | –29.1 | *–36.6* |
| Total nonmanufacturing contribution ($C^{VN} + C_N^{Cov}$) | –16.1 | *–12.2* |
| **Total change in employment growth volatility ($\Delta^T$)** | **–51.5%** | ***–44.0%*** |

*Notes*: This table compares the empirical and model-based decomposition of changes in employment growth volatility during the Great Moderation. See section 2.2 and table 2 for details.

factured inputs. The role of physical investment in the transmission of financial shocks is illustrated in figure 6. It displays the the impulse responses of investment, debt, and dividends to a contractionary financial shock pre- and post-Great Moderation along with the same responses when *only* the financial frictions for the manufacturing sector are reduced. These responses illustrate how manufacturing firms are able to respond to financial shocks by optimally adjusting the composition of their balance sheets when financial frictions are low, but must rely more on output reductions when frictions are high and they are constrained. Reducing financial frictions for only manufacturing firms yields

Table 8: Financial ratio variance decomposition, data and model

| Source | Data | | *Model* | |
|---|---|---|---|---|
| | **Debt-income** | **Dividend-income** | ***Debt-income*** | ***Dividend-income*** |
| $\Delta^C$ | **–33.3%** | **–31.5%** | – | – |
| $\Delta^F = C^{VM} + C^{VM} + C^{Cov}$ | **+365.0%** | **+1,918.3%** | ***+30.4%*** | ***+183.3%*** |
| $C^{VM}$ | +194.3 | +848.0 | *+20.2%* | *+114.8%* |
| $C^{VN}$ | +16.1 | +291.5 | *+0.7%* | *+6.7%* |
| $C^{Cov}$ | +154.6 | +778.9 | *+9.1%* | *+57.7%* |
| $\Delta^T$ | **+210.3%** | **+1,282.8** | ***+30.4%*** | ***+183.3%*** |

*Notes*: This table compares the empirical and model-based decomposition of changes in financial volatility during the Great Moderation. See section 2.3 and table 3 for details.

almost 100% of the reduction in investment volatility and increase in dividend volatility, and most of the increase in debt volatility.

# 5 Conclusion

The Great Moderation was characterized by a reduction in the volatility of real activity and a simultaneous increase in the volatility of firms' balance sheets. Using a statistical decomposition, we first show that the manufacturing sector was primarily responsible for both of these patterns. We next support a causal interpretation for this result by using US investment banking deregulation as a natural experiment. We find that the volatility reductions that followed were larger for states with bigger manufacturing sectors, suggesting that the impact of financial deepening on the manufacturing sector was a crucial component of the Great Moderation.

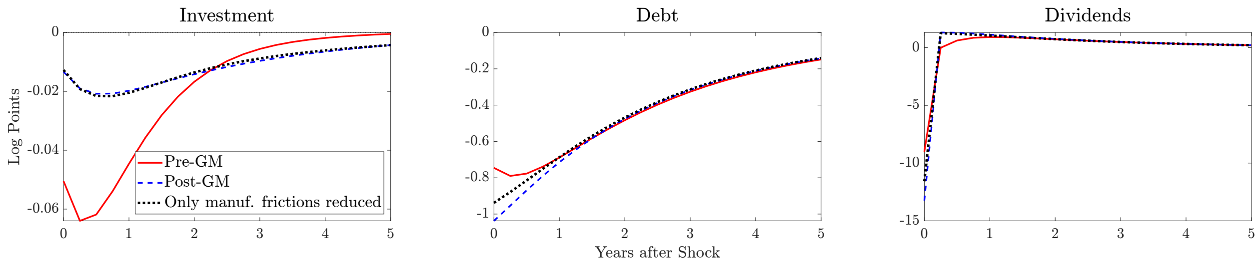


Figure 6: Impulse responses to a contractionary financial shock.

*Notes:* Pre-Great Moderation (red solid) has $\kappa = 0.146$ for each sector; post-Great Moderation (blue dashed) has $\kappa = 0.01$ for each sector. When frictions are reduced only for the manufacturing sector (black dotted), $\kappa = 0.01$ for manufacturing firms and $\kappa = 0.146$ for nonmanufacturing firms. (For investment and dividends, the black dotted line lies almost on top of the blue dashed line.)

To formalize this intuition and consider its quantitative implications, we construct a multisector New Keynesian model with financial frictions. Firms in the model face costs when substituting between debt and equity; when firms cannot costlessly absorb purely financial shocks by changing the composition of their balance sheet, they respond by adjusting production instead. Investment goods—and by extension, the manufacturing sector, which is primarily responsible for producing them—are particularly sensitive to these financial spillovers because their long lifespan and use as collateral make them particularly sensitive to transitory fluctuations. When we simulate the effects of financial deepening in the model by reducing these constraints, we are able to replicate both the aggregate and sector-specific reductions in volatility for both real and financial variables that occurred during the Great Moderation without appealing to any changes in the distributions of fundamental shocks.

Our findings have several important takeaways for researchers and policymakers. The first concerns whether the effects of Great Moderation should be expected to unwind at some point in the future. Unlike exogenous changes in the distributions of fundamental shocks, which can by definition occur at any time, there is little reason to think that the improvements in capital market access for manufacturers that started in the 1980s have unwound. This suggests that a sudden and sustained reversal of the Great Moderation is unlikely. The second key implication of our results is that the benefits of financial deepening operate primarily through a relatively small subset of producers. To the extent that policymakers with limited financial resources want to stabilize business cycles via improved capital market access, our findings suggest that their efforts will be most effective when applied to the producers of long-lived capital goods with volatile demand.

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# Appendix

## A Interstate Banking Deregulation Dates

Table 9: Dates of Interstate Banking Deregulation

| State | Year | State | Year |
|---|---|---|---|
| Alabama | 1987 | Montana | 1993 |
| Alaska | 1982[d] | Nebraska | 1990 |
| Arizona | 1986 | Nevada | 1985 |
| Arkansas | 1989 | New Hampshire | 1987 |
| California | 1987 | New Jersey | 1986 |
| Colorado | 1988 | New Mexico | 1989 |
| Connecticut | 1983 | New York | 1982 |
| Delaware | 1988[a] | North Carolina | 1985 |
| District of Columbia | 1985 | North Dakota | 1988[d] |
| Florida | 1985 | Ohio | 1985 |
| Georgia | 1985 | Oklahoma | 1987 |
| Hawaii | 1996[b] | Oregon | 1986 |
| Idaho | 1985 | Pennsylvania | 1986 |
| Illinois | 1986 | Rhode Island | 1984 |
| Indiana | 1986 | South Carolina | 1986 |
| Iowa | 1991 | South Dakota | 1988[a] |
| Kansas | 1992 | Tennessee | 1985 |
| Kentucky | 1992 | Texas | 1987 |
| Louisiana | 1987 | Utah | 1984 |
| Maine | 1982[c] | Vermont | 1988 |
| Maryland | 1985 | Virginia | 1985 |
| Massachusetts | 1983 | Washington | 1987 |
| Michigan | 1986 | West Virginia | 1988 |
| Minnesota | 1986 | Wisconsin | 1987 |
| Mississippi | 1988 | Wyoming | 1987[d] |
| Missouri | 1986 | | |

*Notes:* a) Following the IBD literature, Delaware and South Dakota are excluded from the main analysis due to their role in the development of the credit card industry. b) Hawaii had not passed legislation allowing out-of-state banking by 1996, which was the first full year which the Interstate Banking and Branching Efficiency Act of 1994 was in effect nationwide. c) Maine first passed legislation allowing interstate banking deregulation in 1978, but only allowed entry from banks based in states that had reciprocal arrangements. This first occurred when New York passed its IBD legislation in 1982, and so we set 1982 as the first effective date for Maine. The results are virtually unchanged if we use 1978 as the starting date for Maine instead. d) Alaska, North Dakota, and Wyoming are identified as outliers in Morgan et al. (2004) and thus excluded from our baseline estimates.

# B Variance decomposition details

Table 10: Employment growth variance decomposition

| | Description | Pre-1984 | Post-1984 | $\Delta$ (pp) | $\Delta$ (%) |
|---|---|---|---|---|---|
| **Total and approximate variance** | | | | | |
| $Var(\Delta A)$ | Actual total employment growth volatility | 4.62 | 2.17 | –2.46 | –53.09% |
| $\hat{Var}(\Delta A)$ | Approx total employment growth volatility | 4.75 | 2.30 | –2.44 | –51.44% |
| $\hat{Var}(\Delta A) - Var(\Delta A)$ | Approximation error | –0.12 | –0.14 | –0.02 | |
| **Fundamental changes** | | | | | |
| $\bar{\gamma}$ | Average mfg employment share (%) | 23.45 | 14.51 | –8.94 | –38.12% |
| $Var(\Delta M)$ | Mfg employment growth variance | 19.08 | 6.91 | –12.17 | –63.80% |
| $Var(\Delta N)$ | Nonmfg employment growth variance | 2.57 | 1.92 | –0.66 | –25.51% |
| $Cov(\Delta M, \Delta N)$ | Covariance between mfg and nonmfg emp growth | 6.09 | 3.05 | –3.04 | –49.89% |
| $Cor(\Delta M, \Delta N)$ | Correlation between mfg and nonmfg emp growth | 0.87 | 0.84 | –0.03 | –3.50% |
| **Laspeyres index calculations** | | | | | |
| $V(\bar{\gamma}^{old})$ | Total volatility holding fixed pre-1984 mfg share | 4.75 | 2.60 | –2.15 | –45.21% |
| $(\bar{\gamma})^2 Var(\Delta M)$ | Approx mfg contribution to total variance | 1.05 | 0.38 | –0.67 | |
| $(1-\bar{\gamma})^2 Var(\Delta N)$ | Approx nonmfg contribution to total variance | 1.51 | 1.12 | –0.38 | |
| $2\bar{\gamma}(1-\bar{\gamma}) Cov(\Delta M, \Delta N)$ | Approx covariance contribution to total variance | 2.19 | 1.10 | –1.09 | |

*Notes:* This table shows the detailed components of our employment growth variance decomposition exercise in section 2.2. The first two columns report the name of each variable and its description. The third and fourth columns show pre- and post-1984 values, while the fifth shows the percentage point difference between the two, and the last column shows the percentage change. The top block shows actual employment growth volatility along with our approximation and the errors between the two. The middle block reports the components of equation 2. The last block of rows shows our approach to calculating changes in "fundamental" volatility. For this exercise, we use the actual values for pre-1984 and post-1984 variance and covariance terms, but hold the manufacturing employment share fixed at its pre-1984 average of 23.45%. The totals shown in the top row of the bottom panel will be equal to the sum of the components shown below, and dividing each component by the total gives the values for $\omega$ used in equation 3.

# C Model appendix

## C.1 Parameter values

Table 11: Model parameter values

| Parameter | Value | Description | Source |
|---|---|---|---|
| $\beta$ | 0.9825 | Discount factor | Jermann and Quadrini (2012) |
| $\theta$ | 0.36 | Capital weight in production function | Jermann and Quadrini (2012) |
| $\alpha$ | 1.8834 | Labor disutility | Jermann and Quadrini (2012) |
| $\delta$ | 0.025 | Capital depreciation rate | Jermann and Quadrini (2012) |
| $\bar{\zeta}$ | 0.1634 | Steady state borrowing limit | Jermann and Quadrini (2012) |
| $\kappa$ | 0.146 | Dividend adjustment cost | Jermann and Quadrini (2012) |
| $\tau$ | 0.35 | Tax rate | Jermann and Quadrini (2012) |
| $\phi^D, \phi^N$ | 50, 100 | Price adjustment costs | Standard |
| $\epsilon$ | 11 | Consumption elasticity of substitution | Standard |
| $\omega$ | 2 | Investment adjustment cost | Howes (2023) |
| $\gamma$ | 3 | Total labor supply elasticity | Standard |
| $\eta$ | 1.18 | Sectoral labor elasticity | Standard |
| $\chi$ | 0.5 | Nondurable weight in labor aggregator | Standard |
| $\phi_\pi, \rho$ | 2, 0.9 | Taylor Rule | Standard |

## C.2 Model details

Firms' optimal choices for labor, material inputs, debt, intermediate and final investment goods, and capital yield the following first order conditions:

$$w_t^i = mpl_t^i \left(1 - \mu_t^i \varphi_{d,t}^i\right) \tag{39}$$

$$p_t^N = mpn_t^i (1 - \mu_t^i \varphi_{d,t}^i) \tag{40}$$

$$p_t^D = mpd_t^i (1 - \mu_t^i \varphi_{d,t}^i) \tag{41}$$

$$p_t^D ID_t^i = P_t^I \psi I_t^i \tag{42}$$

$$p_t^N IN_t^i = P_t^I (1 - \psi) I_t^i \tag{43}$$

$$1 = R_t m_t \left( \frac{\varphi^i_{d,t}}{\varphi^i_{d,t+1}} \right) + \zeta_t \mu^i_t \varphi^i_{d,t} \left( \frac{R_t}{1+i_t} \right) \tag{44}$$

$$\begin{aligned} p^I_t = mk^i_t \exp(v^i_t) \left(1 - \frac{\omega}{2}\left(\frac{I^i_t}{I^i_{t-1}}\right)\right)^2 - \omega\left(\frac{I^i_t}{I^i_{t-1}} - 1\right)\left(\frac{I^i_t}{I^i_{t-1}}\right) \\ + \mathbb{E}_t\left[m_t\left(\frac{\varphi^i_{d,t}}{\varphi^i_{d,t+1}}\right)\exp(v^i_{t+1}) mk^i_{t+1}\omega\left(\frac{I^i_{t+1}}{I^i_t} - 1\right)\left(\frac{I^i_{t+1}}{I^i_t}\right)\right] = 0 \end{aligned} \tag{45}$$

$$mk^i_t = \mathbb{E}_t\left[m_t\left(\frac{\varphi^i_{d,t}}{\varphi^i_{d,t+1}}\right)\left(mk^i_{t+1}(1-\delta) + (1-\mu^i_{t+1}\varphi^i_{d,t+1}) mpk^i_{t+1}\right)\right] + p^d_t \zeta_t \mu^i_t \varphi^i_{d,t} \tag{46}$$

Where $mc^i_t$ is the marginal cost, $mpl^i_t$ is the marginal product of labor, $mpi$ is the marginal product of intermediate inputs from sector $i$, $mpk^i_t$ is the marginal product of capital, and $mk^i_t$ is the Lagrange multiplier on the firm's first order condition for capital.[21]

### C.2.1 Full Set of Equilibrium Conditions

This section shows the set of equations which fully characterize the solution to the model. Equations showing superscripts $i$ indicate two separate equations, one for the durable sector ($D$) and one for the nondurable sector ($N$). All prices are normalized by the aggregate consumption good price index.

$$\frac{1}{C_t} = \lambda_t \tag{47}$$

$$p^N_t C^N_t = \eta^C C_t \tag{48}$$

$$p^D C^D_t = (1-\eta^C) C_t \tag{49}$$

$$\left(C^N_t\right)^{\eta^C}\left(C^D_t\right)^{(1-\eta^C)} = C_t \tag{50}$$

[21] In the case of a single-sector economy with no adjustment costs, $p^I_t = 1$ and $\omega = 0$, and equations 45 and 46 can be combined to yield $1 = \mathbb{E}_t\left[m_t\left(\frac{\varphi^i_{d,t}}{\varphi^i_{d,t+1}}\right)\left(1-\delta+(1-\mu^i_{t+1}\varphi^i_{d,t+1} mpk^i_{t+1}\right)\right]$, which is equivalent to Equation 21 derived from the simplified model in the previous section.

$$w_t^N \lambda_t = \alpha \chi^{\frac{-1}{\gamma}} N_t^{\left(\iota - \frac{1}{\gamma}\right)} \left(N_t^N\right)^{\frac{1}{\gamma}} \tag{51}$$

$$w_t^D \lambda_t = \alpha (1-\chi)^{\frac{-1}{\gamma}} N_t^{\left(\iota - \frac{1}{\gamma}\right)} \left(N_t^D\right)^{\frac{1}{\gamma}} \tag{52}$$

$$N_t = \left[ \chi^{\frac{-1}{\gamma}} \left(N_t^N\right)^{\frac{1+\eta}{\gamma}} + (1-\chi)^{\frac{-1}{\gamma}} \left(N_t^D\right)^{\frac{1+\gamma}{\gamma}} \right]^{\frac{\gamma}{1+\gamma}} \tag{53}$$

$$M_t = \beta \mathbb{E}_t \left[ \frac{\lambda_{t+1}}{\lambda_t} \right] \tag{54}$$

$$\mathbb{E}_t \left[ \frac{M_t (1+i_t)}{\pi_{t+1}} \right] = 1 \tag{55}$$

$$(1+i_t) = \frac{R_t - \tau}{1-\tau} \tag{56}$$

$$w_t^D N_t^D + w_t^N N_t^N + B_t + \varphi(d_t) = \frac{B_{t+1}}{R_t} + C_t + T_t = 0 \tag{57}$$

$$\left((1-\epsilon) p_t^i + (\epsilon) mc_t^i\right) - \phi^i \left(\pi_t^i - 1\right) \pi_t^i + \phi^i \mathbb{E}_t \left[ M_{t+1} \left( \frac{\varphi_{d,t}}{\varphi_{d,t+1}} \right) \left(\pi_{t+1}^i - 1\right) \pi_{t+1}^i \left( \frac{Y_{t+1}^i}{Y_t^i} \right) \right] = 0 \tag{58}$$

$$\beta (i + i_t) = \left(\beta (1 + i_{t-1})\right)^{\rho} \left(\pi_t^{\phi_\pi}\right)^{1-\rho} \exp(e_t^M). \tag{59}$$

$$Y_t^i = A_t X_t^i \left(MN_t^i\right)^{\nu^N} \left(MD_t^i\right)^{\nu^D} \left(K_t^i\right)^{\theta} \left(N_t^i\right)^{1-\theta-\nu^N-\nu^D} \tag{60}$$

$$mpl_t^i = mc_t^i (1-\theta) A_t (K_t^i)^{\theta} (N_t^i)^{-\theta-\nu^N-\nu^D} (MD_t^i)^{\nu^D} (MN_t^i)^{\nu^N} \tag{61}$$

$$mpk_t^i = mc_t^i \theta A_t (K_t^i)^{\theta-1} (N_t^i)^{1-\theta-\nu^N-\nu^D} (MD_t^i)^{\nu^D} (MN_t^i)^{\nu^N} \tag{62}$$

$$w_t^i = mpl_t^i \left(1 - \mu_t^i \phi_{d,t}^i\right) \tag{63}$$

$$p_t^N = mc_t^i \nu^N A_t (N_t^i)^{1-\theta-\nu^N-\nu^D} (K_t^i)^{\theta} (MD_t^i)^{\nu^D} (MN_t^i)^{(\nu^N-1)} \left(1 - \mu_t^i \varphi_{d,t}^i\right) \tag{64}$$

$$p_t^D = mc_t^i \nu^D A_t (N_t^i)^{1-\theta-\nu^N-\nu^D} (K_t^i)^{\theta} (MD_t^i)^{(\nu^D-1)} (MN_t^i)^{\nu^N} \left(1 - \mu_t^i \varphi_{d,t}^i\right) \tag{65}$$

$$p_t^D ID_t^i = p_t^I \psi I_t^i \tag{66}$$

$$p_t^N IN_t^i = p_t^I (1-\psi) I_t^i \tag{67}$$

$$p_t^I = \left(\frac{p_t^D}{\psi}\right)^{\psi} \left(\frac{p_t^N}{1-\psi}\right)^{1-\psi} \tag{68}$$

$$\begin{aligned} p_t^I = mk_t^i \exp(v_t^i) \left(1 - \frac{\omega}{2}\left(\frac{I_t^i}{I_{t-1}^i}\right)\right)^2 - \omega \left(\frac{I_t^i}{I_{t-1}^i} - 1\right)\left(\frac{I_t^i}{I_{t-1}^i}\right) \\ + \mathbb{E}_t \left[ M_t \left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i}\right) \exp(v_{t+1}^i) mk_{t+1}^i \omega \left(\frac{I_{t+1}^i}{I_t^i} - 1\right)\left(\frac{I_{t+1}^i}{I_t^i}\right)\right] = 0 \end{aligned} \tag{69}$$

$$mk_t^i = \mathbb{E}_t \left[ M_t \left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i}\right) \left[ mk_{t+1}^i (1-\delta) + \left(1 - \mu_{t+1}^i \varphi_{d,t+1}^i\right) mpk_{t+1}^i \right]\right] + p_t^I \zeta_t \mu_t \varphi_t^i \tag{70}$$

$$R_t \mathbb{E}_t \left[ M_t \left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i}\right)\right] + \zeta_t \mu_t^i \varphi_{d,t}^i \left(\frac{R_t}{1+i_t}\right) = 1 \tag{71}$$

$$\varphi(d_t^i) = d_t^i - \kappa^i \left(d_t^i - \bar{d}^i\right)^2 \tag{72}$$

$$\varphi_{d,t}^i = 1 + 2\kappa^i \left(d_t^i - \bar{d}^i\right) \tag{73}$$

$$\zeta_t \left(p_t^I K_{t+1}^i - \frac{B_{t+1}^i}{1+i_t}\right) = p_t^i Y_t^i \tag{74}$$

$$p_t^i Y_t^i - p_t^I I_t^i - p_t^D MD_t^i - p_t^N MN_t^i - w_t^i N_t^i - B_t^i + \frac{B_{t+1}^i}{R_t} - \varphi(d_t^i) = 0 \tag{75}$$

$$K_{t+1}^i = (1-\delta) K_t^i + \exp(v_t^i) \left[1 - \frac{\omega}{2}\left(\frac{I_t^i}{I_{t-1}^i} - 1\right)^2\right] I_t^i \tag{76}$$

$$I_t = I_t^D + I_t^N \tag{77}$$

$$K_t = K_t^D + K_t^N \tag{78}$$

$$B_t = B_t^D + B_t^N \tag{79}$$

$$d_t = d_t^D + d_t^N \tag{80}$$

$$Y_t^D = \sum_i \left(ID_t^i + MD_t^i\right) + C_t^D, \quad Y_t^N = \sum_i \left(IN_t^i + MN_t^i\right) + C_t^N \tag{81}$$

$$\pi_t^i = \left( \frac{p_t^i}{p_{t-1}^i} \right) \pi_t \tag{82}$$