

Financial Deepening, Investment Producers, and the Great Moderation*

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Abstract

During the Great Moderation, employment growth volatility plummeted while the volatility of firms' financial structure 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 during this period ("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 without appealing to any changes in the distributions of fundamental shocks. Our results highlight the importance of investment-producing sectors in understanding how financial frictions distort the transmission of shocks.

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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 two robust empirical facts. First, as emphasized 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. Second, despite comprising small shares of output or employment, fundamental changes in the behavior of the manufacturing sector were primarily responsible for both the decreasing volatility of real activity and the increasing volatility of financial activity. 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 next 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 is primarily responsible for producing investment goods. Demand for these long-lived capital goods is more sensitive to financial shocks than demand for non-durable 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 reducing 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 policymakers more effectively target their financial developments. 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 changes

in 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 all show that changes in the distributions of sector-specific shocks play an important role in quantitatively explaining the Great Moderation.

Lastly, this paper builds on the literature documenting the importance of financial shocks in driving business cycles. 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 outsized 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.

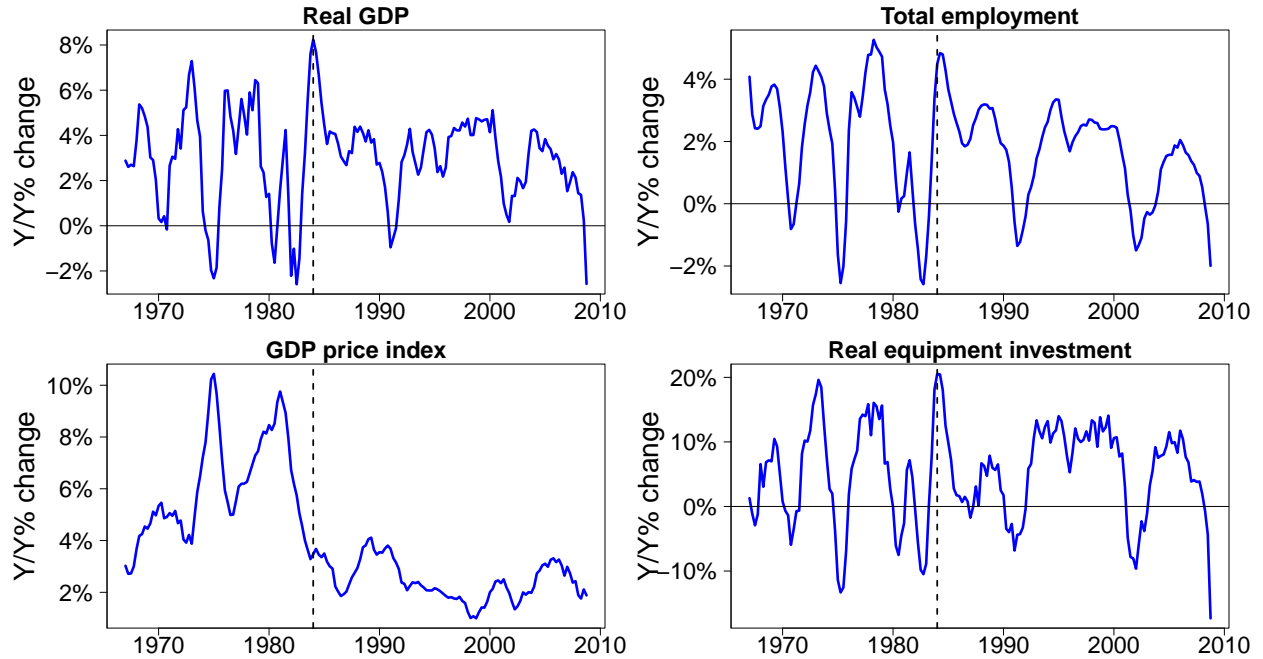


Figure 1: Annual growth rates of economic aggregates

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

	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

Table 1: Magnitude of cyclical fluctuations over time

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.

using the filter of [Hamilton \(2018\)](#). The first three columns show that the decline in the 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 the post-1984 period also saw an *increase* in the volatility of many financial variables. 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

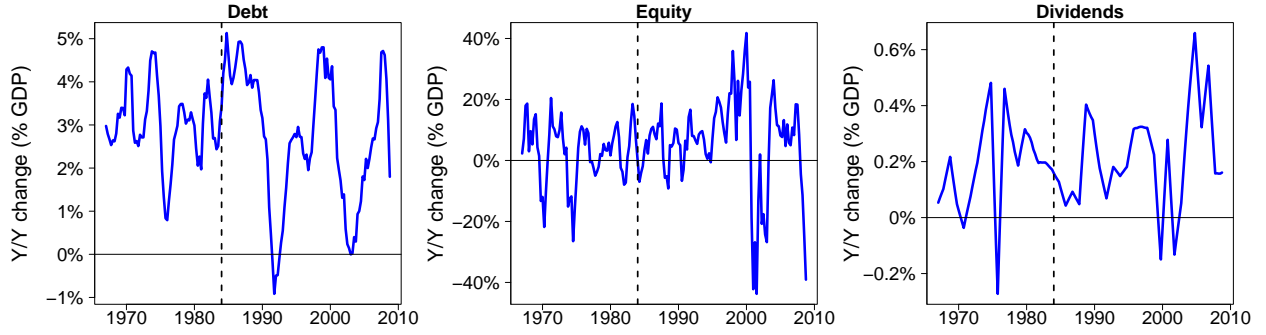


Figure 2: Changes in financial variables

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 \(2000\)](#).

lower variance for all endogenous variables.

In the rest of this section, we document that the manufacturing sector was the primary driver of changes in both real and financial volatility since the Great Moderation. The outsized role of manufacturing in driving nonfinancial volatility is well documented¹, 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 \(2022\)](#).

¹As 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 non-manufacturing employment: $A = M + N$. Using Δ to denote growth rates, we express the percentage change in aggregate employment ΔA as a weighted average of employment growth in each sector: $\Delta A = \gamma \Delta M + (1 - \gamma) \Delta N$, where γ is the manufacturing employment share. From this expression, the variance of ΔA is

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

²We 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 γ changes over time and is not independent of the growth rates ΔM and ΔN , attempts to further decompose this expression will introduce many unwieldy higher-order terms.³ However, a tractable approximation obtains if we assume γ is a constant $\bar{\gamma}$:

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

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 correlation⁴ 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 non-manufacturing 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,

³Howes (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.

⁴While 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.

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

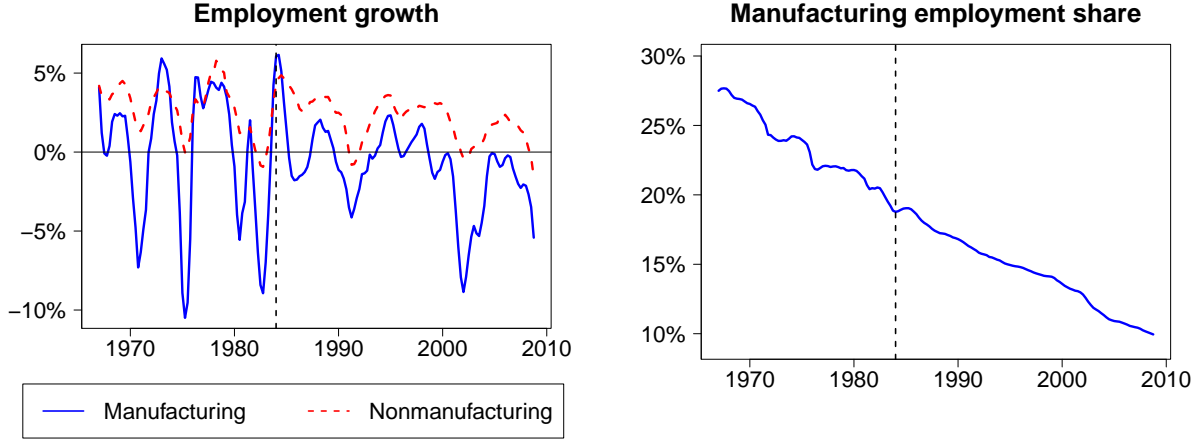


Figure 3: Employment growth rates and shares

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"—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.

This problem is analogous to the one that faces statistical agencies trying to calculate real GDP growth when both prices and quantities move simultaneously. Our goal is to attribute the change in total employment growth volatility Δ^T across its two components: changes in the behavior of each sector—which we refer to as "fundamental volatility", Δ^F , and is analogous to quantities in real GDP calculations—and the mechanical effects that result from changes in the relative size of each sector ("compositional volatility", Δ^C), with $(1 + \Delta^T) = (1 + \Delta^F)(1 + \Delta^C)$.

Next, we further decompose the change in fundamental volatility Δ^F into its components: changes in volatility within each sector ($Var(\Delta M)$ and $Var(\Delta N)$) and the correla-

tion between them. 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 ω :⁶

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

The exercise suggests that the total change in volatility due to the changing manufacturing share Δ^C led to a decline in employment volatility of about 11.3%. The contribution from changes in fundamental volatility Δ^F was much larger, leading do a decline of 45.2% in employment volatility. This fundamental decline can be accounted for with contributions of $C^{VM} = -14.1\text{pp}$, $C^{VN} = -8.1\text{pp}$, and $C^{Cov} = -23.0\text{pp}$. 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 ΔM and ΔN 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

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

an approximate linear decomposition by ignoring changes in the correlation term and allocating the total covariance contribution $C^{Cov} = -23.0\text{pp}$ across the manufacturing and nonmanufacturing sectors in proportion to their growth rates.⁷ The final decomposition of fundamentals (that is, non-compositional changes), which is summarized in table 2, can be written:

$$\Delta^F \approx \underbrace{\underbrace{C^{VM}}_{\text{Direct effect}} + \underbrace{C_M^{Cov}}_{\text{Covariance effect}}}_{\text{Total manufacturing contribution}} + \underbrace{\underbrace{C^{VN}}_{\text{Direct effect}} + \underbrace{C_N^{Cov}}_{\text{Covariance effect}}}_{\text{Total nonmanufacturing contribution}} \quad (4)$$

This decomposition highlights two important facts about the post-1984 decline in employment volatility. The first is that Δ^F is much larger than Δ^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 (-29.1pp) 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

⁷Since the decline in employment volatility was $\frac{63.7}{33.8} = 1.88$ times larger for the manufacturing sector, we can pin down each sector's contribution with the equations $\frac{C_M^{Cov}}{C_N^{Cov}} = 1.88$ and $C^{Cov} = -23.0 = C_M^{Cov} + C_N^{Cov}$.

Table 2: Total employment growth variance decomposition

Source	Contribution
Total changes from composition (Δ^C)	-11.3%
Total changes from fundamentals ($\Delta^F = C^{VM} + C^{VN} + C^{Cov}$)	-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 (Δ^T)	-51.4%

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 (Δ^C); the second row shows the contribution from changes in fundamental volatility (Δ^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%).

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

⁸The 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

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 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.

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.

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

¹⁰Other 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.

- **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 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 γ . 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.

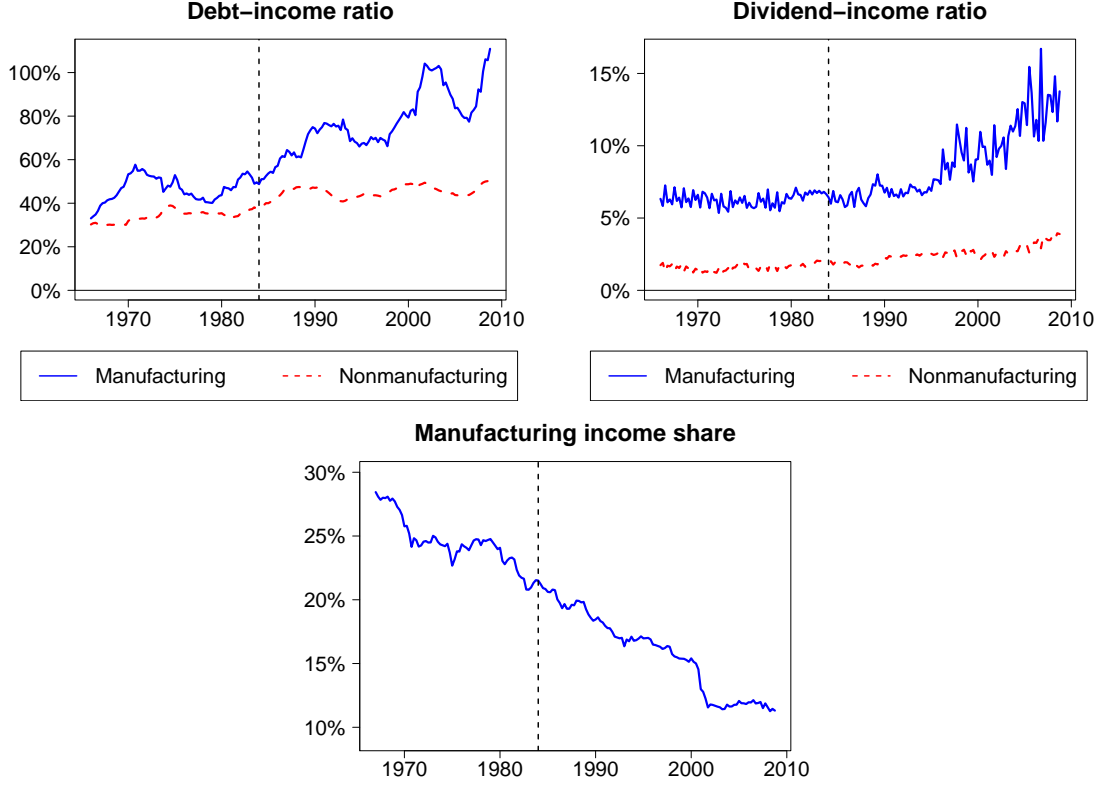


Figure 4: Financial ratios and sector income shares

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 \(2000\)](#).

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 Moderation. First, as with employment, the negative values for Δ^C show that the shrinking of the manufacturing sector contributed to a reduction in volatility. Second, with employment, the fundamental changes within each sector Δ^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

Table 3: Financial ratio variance decomposition

Source	Debt-income	Dividend-income
Δ^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
Δ^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 (Δ^C) shows the change in volatility due to compositional effects; the second row (Δ^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.

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 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

¹¹Focusing 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.

real and financial volatility during the Great Moderation, we next provide evidence that easing financial constraints can parsimoniously generate both patterns.

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:

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

where each observation Y_t^i corresponds to outcome Y in state i at year t ; α^i and δ_t repre-

¹²Recent 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.

sent 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 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.1](#).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-

¹³Recent 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.

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 β pp larger on average in the post-implementation period relative to untreated states. If $\beta < 0$, then states with larger 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 β 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 dispro-

	<i>share</i> 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

Table 4: State-level cyclical fluctuations

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.

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

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

Table 5: Effects of employment shares on IBD transmission

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.

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

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

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 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:

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

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 τ 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 the dividend

disbursement itself plus an additional quadratic cost when its dividend payouts differ from their steady-state level \bar{d} :

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

Firms must also borrow ℓ_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 ζ_t . This leads to a borrowing constraint:

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

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

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

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:

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

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

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 δ is the depreciation

rate.

Let λ and μ 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

$$1 - \lambda \varphi_d(d) = 0, \quad (14)$$

$$\lambda F_n - \lambda w - \mu F_n = 0, \quad (15)$$

$$\mathbb{E} m' V'_k - \lambda + \mu \zeta = 0, \quad (16)$$

$$\mathbb{E} m' V'_b + \frac{\lambda}{R} - \frac{\mu \zeta}{1+i} = 0, \quad (17)$$

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

$$V_k = \lambda [1 - \delta + F_k] - \mu F_k, \quad (18)$$

$$V_b = -\lambda. \quad (19)$$

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

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

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

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

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 μ —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 ($\mathbb{E} [\varphi_d(d')]$) 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

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

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

¹⁵Markets are complete, so households also trade in a full set of contingent claims, which are suppressed in equation 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 the consumption price index. Consumption and labor aggregates are given by

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

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

This consumption aggregator implies that the price index for consumption is

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

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, η^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 dis-

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

count dividend payments from firms, is λ_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:

$$\frac{1}{C_t} = \lambda_t, \quad (28)$$

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

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

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 :

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

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:

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

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:

$$K_{t+1}^i = (1 - \delta)K_t^i + \exp(v_t^i) \left[1 - \frac{\omega}{2} \left(\frac{I_t^i}{I_{t-1}^i} - 1 \right)^2 \right] I_t^i. \quad (33)$$

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 ϵ . Letting p_j^i 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 $Y_j^i = \left(\frac{p_j^i}{p^i} \right)^{-\epsilon} Y^i$.

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

$$\left((1 - \epsilon)p_t^i + (\epsilon)mc_t^i \right) - \phi^i \left(\pi_t^i - 1 \right) \pi_t^i + \phi^i \mathbb{E}_t \left[M_{t+1} \left(\frac{\varphi_{d,t}}{\varphi_{d,t+1}} \right) \left(\pi_{t+1}^i - 1 \right) \pi_{t+1}^i \left(\frac{Y_{t+1}^i}{Y_t^i} \right) \right] = 0. \quad (34)$$

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:

$$\zeta_t \mathbb{E}_t \left(p_t^I K_{t+1}^i - \frac{B_{t+1}^i}{(1 + i_t)} \right) = p_t^i Y_t^i, \quad (35)$$

$$p_t^i Y_t^i - p_t^I I_t^i - p_t^M MD_t^i - p_t^N MN_t^i - w_t N_t^i + \frac{B_{t+1}^i}{R_t} = B_t^i + \varphi(d_t^i). \quad (36)$$

The dividend adjustment cost $\varphi(d_t^i)$ takes the same functional form as shown in equation 9. We assume that all firms face the same aggregate debt constraint parameter ζ_t , but allow for the equity adjustment costs κ^i and steady state dividend payouts \bar{d}^i to poten-

tially 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:

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

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

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

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 κ^i are large, and one in which they

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

Table 6: Model variances with and without financial frictions.

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 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 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

¹⁷Following 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.

¹⁸Recall that financial shocks in the model are captured by shocks to ζ_t the fraction of collateral recoverable by lenders after default.

¹⁹In the model decomposition, the total change is equal to the fundamental change; sector sizes are the

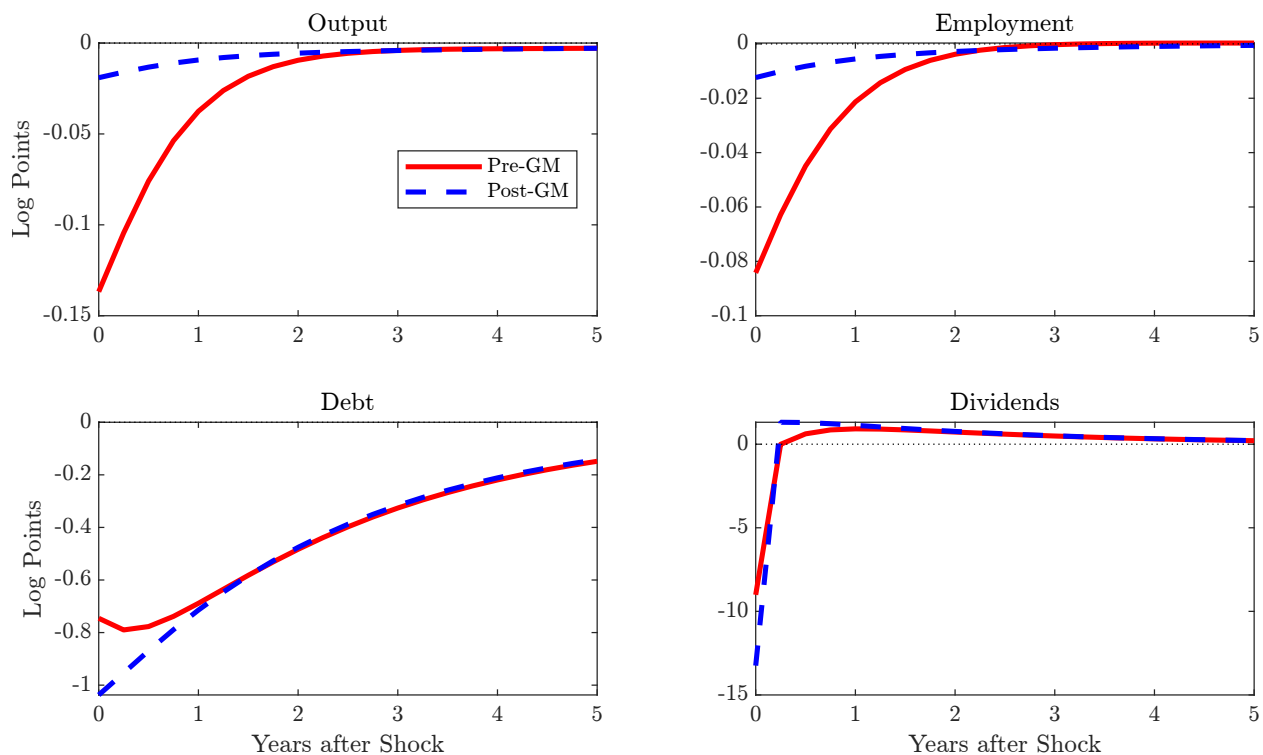


Figure 5: Impulse responses to a contractionary financial shock. Pre-Great Moderation (red solid) has $\kappa = 0.146$ for each sector; post-Great Moderation (blue dashed) has $\kappa = 0.01$ for each sector.

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 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)

same whether financial frictions are high or low, so there is no composition effect.

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

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

Source	Data Employment	Model Employment
Total changes from composition (Δ^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 (Δ^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.

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 manufactured inputs. The role of physical investment in the transmission of financial shocks is illustrated in figure 6. It displays 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 re-

Table 8: Financial ratio variance decomposition, data and model

Source	Data		Model	
	Debt-income	Dividend-income	Debt-income	Dividend-income
Δ^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%
Δ^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.

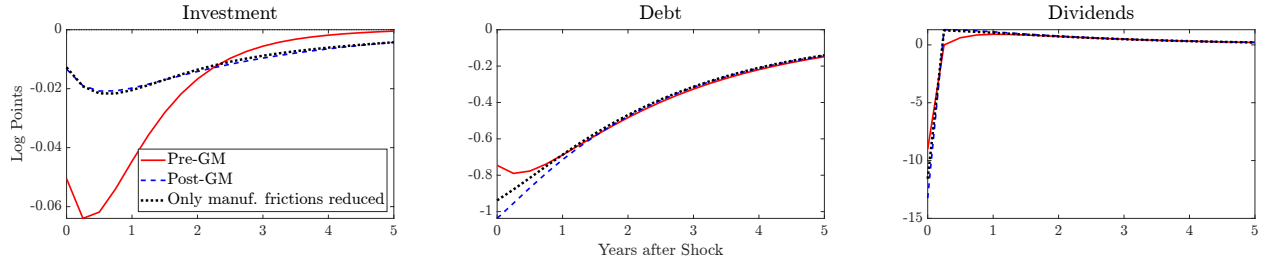


Figure 6: Impulse responses to a contractionary financial shock. Pre-Great Moderation (red solid) has $\kappa = 0.146$ for each sector; post-Great Moderation (blue dashed) has $\kappa = 0.01$ for each sector. When frictions are reduced only for the manufacturing sector (black dotted), $\kappa = 0.01$ 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.)

duced. 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

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.

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, 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 Data and background

A.1 Interstate Banking Deregulation Dates

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		

Table 9: Dates of Interstate Banking Deregulation

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 Robustness checks and additional results

B.1 Variance decomposition details

	Description	Pre-1984	Post-1984	Δ (pp)	Δ (%)
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	

Table 10: Employment growth variance decomposition

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 ω used in equation 3.

C Model appendix

C.1 Parameter values

Parameter	Value	Description	Source
β	0.9825	Discount factor	Jermann and Quadrini (2012)
θ	0.36	Capital weight in production function	Jermann and Quadrini (2012)
α	1.8834	Labor disutility	Jermann and Quadrini (2012)
δ	0.025	Capital depreciation rate	Jermann and Quadrini (2012)
$\bar{\zeta}$	0.1634	Steady state borrowing limit	Jermann and Quadrini (2012)
κ	0.146	Dividend adjustment cost	Jermann and Quadrini (2012)
τ	0.35	Tax rate	Jermann and Quadrini (2012)
ϕ^D, ϕ^N	50, 100	Price adjustment costs	Standard
ϵ	11	Consumption elasticity of substitution	Standard
ω	2	Investment adjustment cost	Howes (2023)
γ	3	Total labor supply elasticity	Standard
η	1.18	Sectoral labor elasticity	Standard
χ	0.5	Nondurable weight in labor aggregator	Standard
ϕ_π, ρ	2, 0.9	Taylor Rule	Standard

Table 11: Model parameter values

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:

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

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

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

$$p_t^D ID_t^i = P_t^I \psi I_t^i \quad (42)$$

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

$$1 = R_t m_t \left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i} \right) + \zeta_t \mu_t^i \varphi_{d,t}^i \left(\frac{R_t}{1 + i_t} \right) \quad (44)$$

$$p_t^I = mk_t^i \exp(v_t^i) \left(1 - \frac{\omega}{2} \left(\frac{I_t^i}{I_{t-1}^i} \right) \right)^2 - \omega \left(\frac{I_t^i}{I_{t-1}^i} - 1 \right) \left(\frac{I_t^i}{I_{t-1}^i} \right) \\ + \mathbb{E}_t \left[m_t \left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i} \right) \exp(v_{t+1}^i) mk_{t+1}^i \omega \left(\frac{I_{t+1}^i}{I_t^i} - 1 \right) \left(\frac{I_{t+1}^i}{I_t^i} \right) \right] = 0 \quad (45)$$

$$mk_t^i = \mathbb{E}_t \left[m_t \left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i} \right) \left(mk_{t+1}^i (1 - \delta) + (1 - \mu_{t+1}^i \varphi_{d,t+1}^i) mpk_{t+1}^i \right) \right] + p_t^d \zeta_t \mu_t^i \varphi_{d,t}^i \quad (46)$$

Where mc_t^i is the marginal cost, mpl_t^i is the marginal product of labor, mpi is the marginal product of intermediate inputs from sector i , mpk_t^i is the marginal product of capital, and mk_t^i 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.

$$\frac{1}{C_t} = \lambda_t \quad (47)$$

$$p_t^N C_t^N = \eta^C C_t \quad (48)$$

$$p_t^D C_t^D = (1 - \eta^C) C_t \quad (49)$$

$$(C_t^N)^{\eta^C} (C_t^D)^{(1-\eta^C)} = C_t \quad (50)$$

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

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

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

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

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

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

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

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

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

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

$$Y_t^i = A_t X_t^i \left(M N_t^i \right)^{\nu^N} \left(M D_t^i \right)^{\nu^D} \left(K_t^i \right)^\theta \left(N_t^i \right)^{1-\theta-\nu^N-\nu^D} \quad (60)$$

$$m p l_t^i = m c_t^i (1 - \theta) A_t (K_t^i)^\theta (N_t^i)^{-\theta-\nu^N-\nu^D} (M D_t^i)^{\nu^D} (M N_t^i)^{\nu^N} \quad (61)$$

$$m p k_t^i = m c_t^i \theta A_t (K_t^i)^{\theta-1} (N_t^i)^{1-\theta-\nu^N-\nu^D} (M D_t^i)^{\nu^D} (M N_t^i)^{\nu^N} \quad (62)$$

$$w_t^i = m p l_t^i \left(1 - \mu_t^i \phi_{d,t}^i \right) \quad (63)$$

$$p_t^N = m c_t^i \nu^N A_t (N_t^i)^{1-\theta-\nu^N-\nu^D} (K_t^i)^\theta (M D_t^i)^{\nu^D} (M N_t^i)^{(\nu^N-1)} \left(1 - \mu_t^i \phi_{d,t}^i \right) \quad (64)$$

$$p_t^D = m c_t^i \nu^D A_t (N_t^i)^{1-\theta-\nu^N-\nu^D} (K_t^i)^\theta (M D_t^i)^{(\nu^D-1)} (M N_t^i)^{\nu^N} \left(1 - \mu_t^i \phi_{d,t}^i \right) \quad (65)$$

$$p_t^D I D_t^i = p_t^I \psi I_t^i \quad (66)$$

$$p_t^N I N_t^i = p_t^I (1 - \psi) I_t^i \quad (67)$$

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

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

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

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

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

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

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

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

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

$$I_t = I_t^D + I_t^N \quad (77)$$

$$K_t = K_t^D + K_t^N \quad (78)$$

$$B_t = B_t^D + B_t^N \quad (79)$$

$$d_t = d_t^D + d_t^N \quad (80)$$

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

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