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 drove both patterns and provide causal evidence linking these effects to improved access to capital markets. To explain our findings, we construct a multisector model with financially constrained producers. Easing financial constraints in the model parsimoniously replicates the aggregate and sector-specific changes in both real and financial volatility during the Great Moderation, and this result is driven by manufacturing's outsized role in producing investment. Our results highlight the importance of investment producers 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 show that technological and regulatory developments that improved access to capital markets—a process known as financial deepening—played a crucial role in the Great Moderation by easing firms' financial constraints. We show that this channel operated primarily through the manufacturing sector and that it was a direct consequence of manufacturing's central role in the production of durable capital goods.

Our approach is motivated by the fact that firms' financial positions 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 employment and income. 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 next exploit state-level variation in credit supply resulting from the staggered deregulation of US interstate banking that began in the late 1970s. 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 36% of the total post-Great Moderation decline in the average magnitude of cyclical fluctuations for employment and 60% 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 financial shocks, nonfinancial variables will be forced to adjust instead. In addition to creating an important role for shocks originating entirely within the financial sector in driving output, employment, and investment, the addition of financial constraints in the model also meaningfully changes the real effects of monetary policy shocks.

Sectoral heterogeneity is crucial for understanding how changes in financial structure affect the transmission of shocks in the model. We calibrate our model to match the investment and consumption network data developed in vom Lehn and Winberry (2022), who show that the manufacturing sector plays an outsized role in producing investment goods. These long-lived capital goods will have a much higher demand elasticity than nondurable goods because most of the benefits from investing today come from the present discounted value of future reductions in marginal cost, which causes employment and output in the durable sector to exhibit larger responses to shocks.

We simulate financial deepening in the model by easing financial constraints symmetrically across all sectors. The most quantitatively important consequence of this change is to allow the manufacturing sector to absorb financial shocks almost entirely by adjusting the composition of debt and equity, rather than adjusting output and employment, which leads to large reductions in aggregate volatility. While easing financial constraints also benefits nonmanufacturing firms, the impact is much smaller, because monetary and financial shocks have much smaller effects on this sector to begin with. 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.

The model allows us to conduct counterfactual exercises to verify the role of investment goods in driving these results. We show that easing financial constraints on the manufacturing sector alone can account for both the attenuated response of investment and the increased response of financial variables in response to both financial and monetary policy shocks. We also show that diminishing the unique role of investment goods, either by increasing depreciation rates or decreasing the capital share in production, reduces the effects of financial deepening on volatility.

Our results have three important implications for researchers and policymakers. First, a better understanding of underlying drivers of the Great Moderation can yield insights into whether its effects will continue. To the extent that firm access to capital markets has improved 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 reduce firms' financial frictions 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. Finally, our results suggest that changes in the composition of investment, such as a growing role for intangible capital goods like software or intellectual property, can change how the economy responds to financial deepening.

Literature review. We build on the 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 their propagation. One prominent example 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.

Our proposed explanation—changing financial frictions for investment producers—puts this paper 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 suggest 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." We take exactly this approach and find that investment-producing sectors are the primary beneficiaries of easing financial frictions.

By emphasizing the role of the manufacturing sector in driving the Great Moderation, our paper also complements recent work showing that changes in the distributions of sector-specific shocks led to changes in the properties of business cycles over the past several decades including Foerster, Sarte, and Watson (2011), Garin, Pries, and Sims (2018), and vom Lehn and Winberry (2022). Our emphasis on the manufacturing sector is consistent with Carvalho and Gabaix (2013), who show that a shrinking manufacturing sector reduced the volatility of real GDP. Their channel is not mutually exclusive with our proposed explanation, and our empirical exercises confirm that these mechanical compositional changes did indeed contribute to the reduction in real volatility during the Great Moderation. However, our results suggest that this mechanism alone cannot fully account for the Great Moderation, nor can it explain why manufacturing's contribution to financial volatility increased even as the sector shrank.

Lastly, this paper builds on the literature studying how financial constraints distort business cycles. Our primary theoretical contribution is to incorporate the frictions used in Jermann and Quadrini (2012) into a multisector New Keynesian model that features interactions between monetary policy and financial variables. We develop several novel empirical measures of financial activity for the manufacturing sector 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 sectoral heterogeneity across non-financial dimensions—such as the ultimate uses of output produced by different sectors—can lead to qualitatively different responses to changes in financial frictions.

We proceed as follows. Section 2 provides background on—and documents manufacturing's outsized role in driving—the Great Moderation. Section 3 presents causal evidence for the importance of the manufacturing sector in the transmission of financial deepening to volatility. Section 4 develops a multisector model with heterogeneous financial constraints to analyze the quantitative implications of easing firm financial frictions. Section 5 discusses the consequences of our findings for researchers and policymakers. Finally, section 6 concludes.

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).

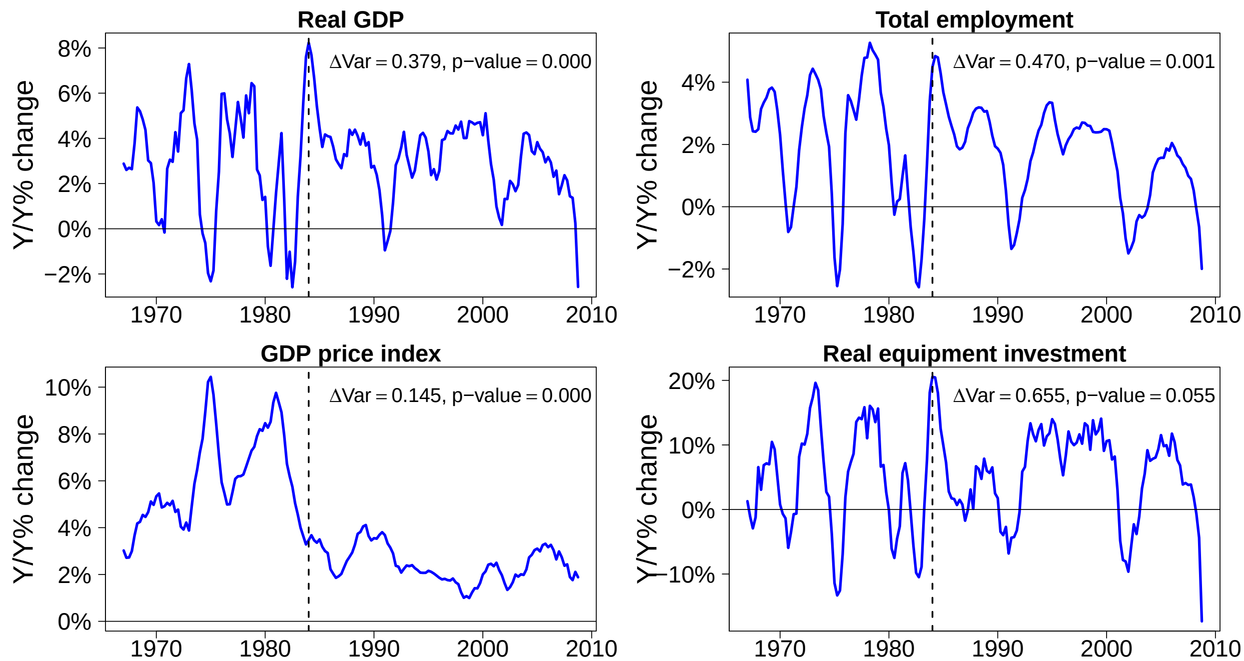

Figure 1: Annual growth rates of economic aggregates

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). In the top-right corner we report ΔVar, the ratio of the post-1984 sample variance to the pre-1984 sample variance, along with the corresponding p-value from a two-sided F-test of the null hypothesis that they are equal (ΔVar=1). Source: BEA National Income and Product Accounts and BLS Current Employment Statistics.

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 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 volatility.

While this pattern has been documented extensively and can be observed to varying degrees across most nonfinancial variables, less well known is the fact that most financial variables became *more* volatile after 1984. This can be seen in figure 2, which plots

Table 1: Magnitude of cyclical fluctuations over time

	GDP	Consumption	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. Source: BEA National Income and Product Accounts and BLS Current Employment Statistics.

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. As Jermann and Quadrini (2009) emphasized, 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 show 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 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

[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%.

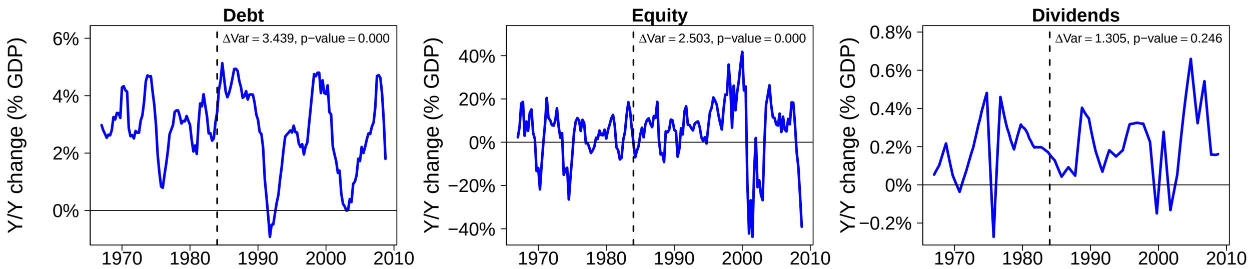

Figure 2: Changes in financial variables

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). In the top-right corner we report ΔVar, the ratio of the post-1984 sample variance to the pre-1984 sample variance, along with the corresponding p-value from a two-sided F-test of the null hypothesis that they are equal (ΔVar=1).

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 outsized importance of the manufacturing sector in producing investment goods documented in vom Lehn and Winberry (2022).

2.2 Manufacturing and employment volatility

In this section, we use a variance decomposition to argue that the manufacturing sector accounts for most of the decline in employment volatility during the Great Moderation.[2] Changes to specific sectors of the economy can affect aggregate volatility through two possible channels: *Fundamental changes* alter the volatility of a sector while leaving its relative size unchanged, while *compositional changes* hold the properties of each sector fixed

[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 changing their relative sizes. Disentangling these two channels is crucial for interpreting our main theoretical results—which generate exclusively fundamental changes in our model—because the manufacturing sector steadily shrank as a share of the total economy throughout our sample period. Our decomposition suggests that a decline in the volatility of manufacturing employment, rather than a smaller manufacturing sector, was the primary force behind the reduction in employment volatility observed during the Great Moderation.

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 more than 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

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

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 $\bar{\gamma}$:

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

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 covariance between each sector's employment growth ($Cov(\Delta M, \Delta N)$).

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.[4]

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, 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 changes in "fundamental volatility" ΔF—that is, those that would have taken place even if the sectoral composition of the

[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] Table 15 in the appendix shows the detailed components of our approximation.

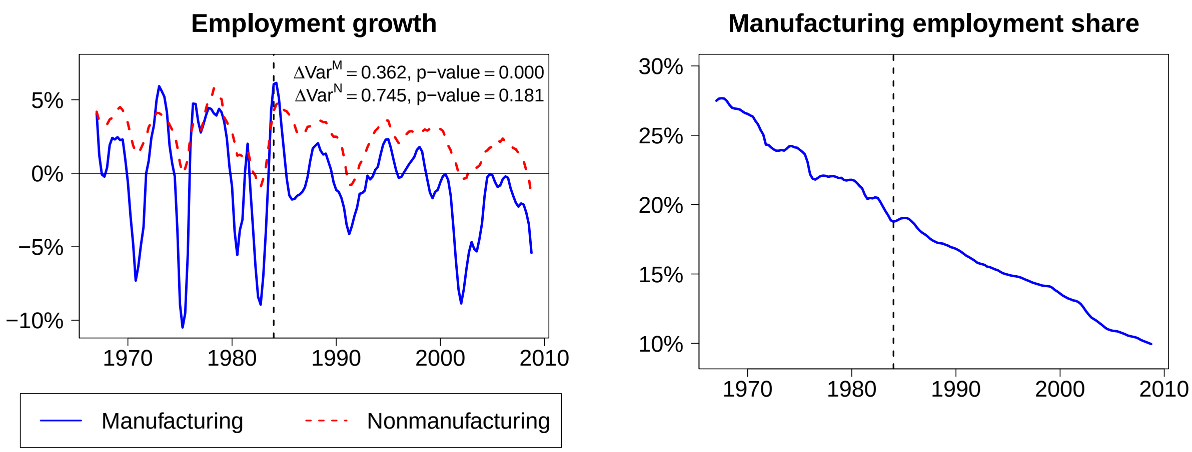

Figure 3: Employment growth rates and shares

Notes: The left panel plots the year-over-year quarterly growth rates for manufacturing (solid blue) and nonmanufacturing (dashed red) employment. The 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). In the top-right corner we report $\Delta\text{Var}^{\text{M}}$ and $\Delta\text{Var}^{\text{N}}$, the ratios of the post-1984 sample variance to the pre-1984 sample variance for the manufacturing and nonmanufacturing sectors, along with the corresponding p-values from two-sided F-tests of the null hypothesis that they are equal (ΔVar=1). The right panel plots the manufacturing share of total employment. Source: BLS Current Employment Statistics.

economy had remained fixed—from the purely mechanical changes resulting from manufacturing's lower weight in total employment growth ("compositional volatility", Δ^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 Δ^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 its "nominal" share of total volatility in the pre-GM period ω:[5]

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

$$+ \underbrace{(1 - \omega^M - \omega^N) \left[\left(\frac{Cor^{new}(\Delta M, \Delta N)}{Cor^{old}(\Delta M, \Delta N)} \right) \left(\sqrt{\frac{Var^{new}(\Delta M)}{Var^{old}(\Delta M)}} \right) \left(\sqrt{\frac{Var^{new}(\Delta N)}{Var^{old}(\Delta N)}} \right) - 1 \right]}_{\text{Covariance contribution}} \tag{3}$$

The exercise shows that the changing manufacturing share Δ^C led to a decline in employment volatility of about 11.3%.[6] The change in fundamental volatility Δ^F of 45.2% was much larger and can be broken down into contributions from $C^{VM} = -14.1$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 pre-GM, 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}. The sector-specific variance terms enter the covariance contribution nonlinearly, but we obtain an approximate linear decomposition by ignoring changes in the correlation term—which was virtually unchanged across the pre-GM and post-GM periods—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 of

[5]These expressions are shown in the bottom panel of table 15. For the manufacturing sector, for example, this share will be $\omega^M = \frac{(\bar{\gamma})^2 Var(\Delta M)}{\widehat{Var}(\Delta A)} = \frac{(0.235)^2 \times 19.08}{4.75} = 0.22$.

[6]Note that change in total volatility Δ^T satisfies $(1 + \Delta^T) = (1 + \Delta^F) \times (1 + \Delta^C)$, where Δ^T is calculated using the approximation in equation 2.

[7]Since the decline in employment volatility was 2.49 times larger for the manufacturing sector (63.7%) than the nonmanufacturing sector (25.5%), we can pin down each sector's contribution with the equations $\frac{C_M^{Cov}}{C_N^{Cov}} = 2.49$ and $C^{Cov} = -23.0 = C_M^{Cov} + C_N^{Cov}$.

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

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

This decomposition highlights two important facts about the post-1984 decline in employment volatility. First, 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. Second, the contribution from the manufacturing sector (-30.5pp) accounted for more than 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]

[8] The Internal Revenue Service Statistics of Income data report annual aggregate income and balance sheet information by industry starting in the 1990s. The US financial accounts provide a long time series of quarterly data, but do not contain information about specific industries. Aggregate quarterly financial series can be constructed from firm-level Compustat data, but these would omit smaller private firms.

Table 2: Total employment growth variance decomposition

Source	Contribution
Total changes from composition (Δ^C)	**–11.3%**
Total changes from fundamentals ($\Delta^F = C^{VM} + C^{VM} + C^{Cov}$)	**–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^{Cov}_M)	–16.4
Approx. nonmanufacturing covariance effect (C^{Cov}_N)	–6.6
Total manufacturing contribution ($C^{VM} + C^{Cov}_M$)	–30.5
Total nonmanufacturing contribution ($C^{VN} + C^{Cov}_N$)	–14.7
Total change in employment growth volatility (Δ^T)	**–51.4%**

Notes: This table shows the decomposition of changes in employment growth volatility during the Great Moderation from equation 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 (-30.5pp) accounted for roughly two-thirds of the decline in total fundamental volatility (-45.2%). The total change shown at the bottom satisfies $(1 + \Delta^T) = (1 + \Delta^F) \times (1 + \Delta^C)$, with Δ^T obtained from the approximation in equation 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 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 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 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

[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.

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:

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

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:

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

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 Moderation. First, because financial variables are consistently more volatile for manufacturing firms, the shrinking of the manufacturing sector over time reduces volatility,

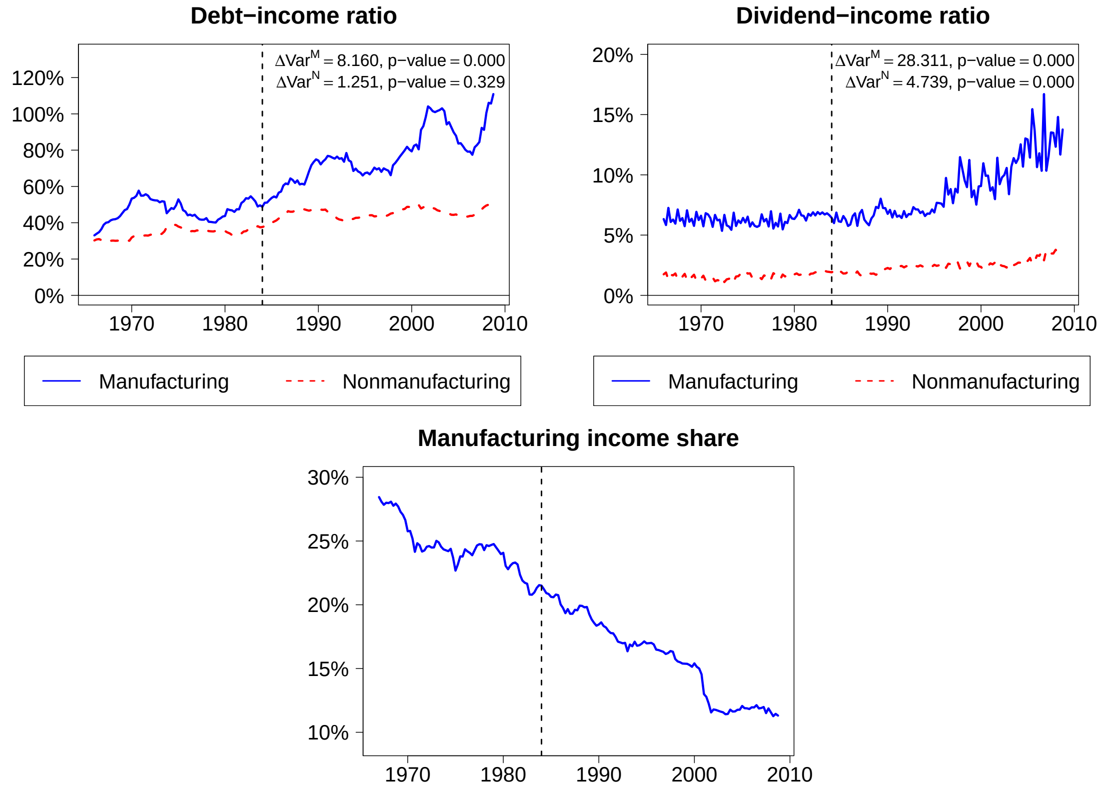

Figure 4: Financial ratios and sector income shares

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). In the top-right corner we report $\Delta \text{Var}^{\text{M}}$ and $\Delta \text{Var}^{\text{N}}$, the ratios of the post-1984 sample variance to the pre-1984 sample variance for the manufacturing and nonmanufacturing sectors, along with the corresponding p-values from two-sided F-tests of the null hypothesis that they are equal (ΔVar=1). Source: Census Quarterly Financial Report, Federal Reserve US Financial Accounts, and authors' calculations.

leading to negative values for Δ^C. Second, the fundamental changes within each sector Δ^F contributed to 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 change in fundamental 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,

Table 3: Financial ratio variance decomposition

Source	Debt-income	Dividend-income
Δ^C	**–33.3%**	**–31.5%**
$\Delta^F = C^{VM} + C^{VN} + C^{Cov}$	**+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 increase in dividend volatility than the nonmanufacturing sector and 12 times more for the increase in debt volatility. The total change shown at the bottom satisfies $(1 + \Delta^T) = (1 + \Delta^F) \times (1 + \Delta^C)$, with Δ^T obtained from the approximation in equation 2.

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 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; throughout the 1980s and early 1990s, almost every US state passed IBD legislation, until ultimately the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 removed these restrictions nationwide. Jayaratne and Strahan (1996) first showed that this deregulation led to an expansion in economic activity, and subsequent studies including Morgan, Rime, and Strahan (2004) and Acharya, Imbs, and Sturgess (2011) showed that IBD also led to reductions in state-level nonfinancial volatility. 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; α^i and δ_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.[12] 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] We report similar results in the appendix using the estimator developed in De Chaisemartin and d'Haultfoeuille (2024), which accounts for bias in the presence of heterogenous treatment effects.

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. Because we use this fixed value across all time periods for each state, the coefficient for $share^i$ will be perfectly collinear with the state fixed effects, and thus we omit it from our results. In Appendix A.2, we report very similar estimates using either the actual manufacturing share for each state in each period or the share immediately prior to deregulation.

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.[13] 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 Wyoming as outliers in our baseline specification, though this is not crucial for the main results. The deregulation dates are shown in appendix A.[14]

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 log real GSP, log employment, and the level of the unemployment rate (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.

[13] Our empirical approach uses data through 2008 to maintain consistency in the time periods used to calculate the trend/cycle decomposition. However, we obtain similar results when stopping in 1996 (the first full year that the Riegle-Neal Interstate Banking and Branching Efficiency Act, which removed IBD restrictions nationwide, went into effect).

[14] 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.

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 βpp 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. Estimates of β are shown in table 5 with the outcome for each column labeled at the top.

Our results suggest that an additional one percentage point increase in a state's pre-IBD manufacturing employment share led to an additional reduction in the average magnitude of that state's cyclical GSP deviations as a share of GSP 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 (roughly 7pp) reduces the magnitude of that state's average cyclical GSP deviation as a share of GSP by 0.87pp.[15] This represents more than one-third of the standard deviation across the entire sample, and more than 60% 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 0.45pp and 0.18pp, respectively. These values represent roughly 36% of the total post-1984 change for employment and 23%

[15]Given our results in section 2.3, we would ideally also want to show that higher manufacturing shares led to greater increases in the volatility of state-level business lending following exogenous increases in credit supply. However, because the entire goal of IBD was to allow banks to provide financing to firms in other states, it is likely that some of these effects would show up in other states. Nonetheless, we do find that a higher manufacturing employment share leads to a statistically insignificant increase in the volatility of commercial and industrial lending. These results are consistent with Herrera, Minetti, and Schaffer (2024), who show that credit reallocation increased for public firms after states implemented IBD.

Table 4: State-level cyclical fluctuations

	$share^i$ (pp)	RGSP (%)	Employment (%)	UR (pp)
	Entire sample (1973-2008)			
5th percentile	4.59	0.28	0.18	0.08
25th percentile	12.18	1.33	0.89	0.38
Mean	17.48	3.16	2.17	0.99
Median	17.00	2.69	1.79	0.80
Standard deviation	7.05	2.37	1.73	0.84
75th percentile	22.50	4.49	3.00	1.35
95th percentile	28.35	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 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. Source: BLS Current Employment Statistics, BLS Local Area Unemployment Statistics, and BEA GDP by State.

Table 5: Effects of employment shares on IBD transmission

	RGSP	Employment	Unemployment rate
IBD_t^i	1.320***	0.223	0.093
	(0.479)	(0.649)	(0.114)
$IBD_t^i \times share^i$	-0.124***	-0.064**	-0.025***
	(0.028)	(0.031)	(0.007)
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, and is not reported because it will be perfectly collinear with the state fixed effects. 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. Employment data come from BLS Current Employment Statistics.

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 how easing financial constraints contributed to the Great Moderation; while they study how financial deepening can smooth shocks across states, we instead focus on its role in smoothing shocks 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. This experiment provides a useful source of identifying variation to provide causal evidence that financial deepening can generate the patterns documented in section 2.

By allowing firms to borrow from a wider pool of lenders, IBD plausibly made it easier for firms to adjust their borrowing in response to shocks. This mechanism aligns closely with our main theoretical exercise in the next section, in which we simulate the effects of financial deepening by reducing the costs of adjusting their capital structure. However, IBD was not the only change in financial markets that occurred during the 1980s; other important regulatory and technological developments included syndicated loans, junk bonds, securitization, and elimination of interest caps under Regulation Q.[16] It is ultimately this broader concept of financial deepening, rather than IBD specifically, that we intend to capture with our model in the next section.

4 Model

This section presents a medium-scale New Keynesian model[17] that can match the empirical patterns documented in sections 2 and 3 through the inclusion of two key features. The first is a multisector input-output production structure in which the manufacturing sector is the most important producer of capital goods as in vom Lehn and Winberry (2022). The second is a financial friction based on Jermann and Quadrini (2012) that prevents firms from costlessly adjusting their capital structure. Financial shocks in the model have much larger effects on the manufacturing sector because demand for capital goods is highly elastic. Reducing financial frictions allows the manufacturing sector to absorb these shocks by adjusting its debt and equity instead of its output and employment, leading to reductions in real volatility and increases in financial volatility. Manufacturing's importance in the production of investment is crucial for this mechanism; as we show in section 5, either a shorter lifespan for investment goods as productive capital (a higher depreciation rate) or a lower capital share in the production function will both diminish the absolute changes in aggregate real and financial volatility.

[16] Frame and White (2004) provide a thorough review of the empirical literature studying financial innovations.

[17] We use a New Keynesian model because, as we show in section 5, financial frictions meaningfully distort the transmission of monetary policy shocks.

4.1 Households

Households get utility from consuming output from both the manufacturing (M) and nonmanufacturing (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.[18] The representative household's problem is

$$\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log(C_t) - \alpha \frac{L_t^{1+\gamma}}{1+\gamma} \right], \tag{8}$$

$$\text{subject to} \qquad P_t C_t + \frac{B_{t+1}}{(1+i_t)} = B_t + W_t^N L_t^N + W_t^M L_t^M + P_t d_t + P_t T_t, \tag{9}$$

where superscripts N and M denote nonmanufacturing and manufacturing, respectively, C_t and L_t are consumption and labor aggregates, B_t denotes maturing nominal bonds, i_t is the nominal interest rate, L_t^i and W_t^i are labor hours and nominal wages in each sector, d_t is real dividend payments, T_t is real net lump-sum transfers (including rebated adjustment costs, tax revenues, and the corporate interest subsidy), and P_t is the consumption price index. Consumption and labor aggregates are given by

$$C_t = \left(C_t^M\right)^{\sigma} \left(C_t^N\right)^{1-\sigma}, \tag{10}$$

$$L_t = \left[\chi^{\frac{-1}{\eta}} \left(L_t^M\right)^{\frac{1+\eta}{\eta}} + (1-\chi)^{\frac{-1}{\eta}} \left(L_t^N\right)^{\frac{1+\eta}{\eta}} \right]^{\frac{\eta}{1+\eta}}. \tag{11}$$

This consumption aggregator implies that the price index for consumption is

$$P_t = \left(\frac{P_t^M}{\sigma}\right)^{\sigma} \left(\frac{P_t^N}{1-\sigma}\right)^{1-\sigma}, \tag{12}$$

[18] Markets are complete, so households also trade in a full set of contingent claims, which are suppressed in equation 9.

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, σ will represent the household consumption expenditure share on manufactured goods, so that $p_t^M C_t^M = \sigma C_t$ and $p_t^N C_t^N = (1-\sigma)C_t$, 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 11 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. The Lagrange multiplier on the budget constraint, which is used to discount dividend payments from firms, is λ_t. In this framework, the stochastic discount factor Λ for real payments can be expressed as $\Lambda_t = \beta \mathbb{E}_t \left[\frac{\lambda_{t+1}}{\lambda_t}\right]$. Household optimality conditions for consumption, labor supply, and nominal bond holdings are:

$$\frac{1}{C_t} = \lambda_t, \tag{13}$$

$$\lambda_t w_t^i = \alpha \left(\chi^i\right)^{\frac{-1}{\eta}} \left(L_t\right)^{\gamma - \frac{1}{\eta}} \left(L_t^i\right)^{\frac{1}{\eta}}, \tag{14}$$

$$1 = \mathbb{E}_t \left[\Lambda_t \frac{1+i_t}{\pi_{t+1}}\right], \tag{15}$$

where $\chi^M = \chi$, $\chi^N = (1-\chi)$, and aggregate labor L_t is defined in Equation 11.

4.2 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 L_t^i, capital K_t^i, and manufactured intermediate materials MM_t^i, with aggregate and sector-specific productivity terms A_t and X_t^i:

$$Y_t^i = A_t X_t^i \left(MM_t^i\right)^{\nu} \left(K_t^i\right)^{\theta} \left(L_t^i\right)^{1-\theta-\nu}. \tag{16}$$

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:

$$I_t^i = \left(IM_t^i\right)^{\psi} \left(IN_t^i\right)^{1-\psi}. \tag{17}$$

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:

$$K_{t+1}^i = (1-\delta)K_t^i + \exp(v_t^i)\left[1 - \frac{\omega}{2}\left(\frac{I_t^i}{I_{t-1}^i} - 1\right)^2\right] I_t^i. \tag{18}$$

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.[19] This leads to the following sector-specific pricing opti-

[19]We parameterize these costs by slightly attenuating the values in Howes (2023) to account for the presence of nondurable sectors within manufacturing while still allowing for investment goods to have greater price flexibility.

mality conditions, with mc_t^i representing each sector's marginal cost:

$$\left((1-\epsilon)p_t^i + (\epsilon)mc_t^i\right) - \phi^i\left(\pi_t^i - 1\right)\pi_t^i + \phi^i\mathbb{E}_t\left[\Lambda_t\left(\frac{\varphi_{d,t}}{\varphi_{d,t+1}}\right)\left(\pi_{t+1}^i - 1\right)\pi_{t+1}^i\left(\frac{Y_{t+1}^i}{Y_t^i}\right)\right] = 0. \tag{19}$$

4.3 Financial constraints

In addition to the adjustment costs for real investment and changes in nominal prices, firms in each sector also face financial constraints on their production decisions. Following Jermann and Quadrini (2012), we include two separate financial frictions: a borrowing (collateral) constraint on intratemporal loans and dividend adjustment costs. Firms must borrow intratemporally at zero interest their flow production costs, reflecting limited enforceability of debt contracts—firms cannot borrow beyond a level that can be secured by their future collateral—while the dividend adjustment cost creates a wedge between internal and external finance by penalizing large deviations in payouts. While this adjustment cost is modeled as applying only to dividends, Jermann and Quadrini (2012) emphasize that it can also be thought of as applying to debt[20], which links this mechanism to our empirical results studying IBD in the previous section.

Formally, the collateral constraint requires that expected debt obligations not exceed a fraction of the firm's future collateral value. If a firm were to default, creditors can only recover an exogenous fraction ζ_t of the firm's capital stock net of outstanding debt. This implies the following constraint:

$$p_t^i Y_t^i \;\leq\; \zeta_t \mathbb{E}_t\left(p_t^I K_{t+1}^i - \frac{B_{t+1}^i}{1+i_t}\right), \tag{20}$$

where the right-hand side is the pledgeable value of collateral (the next period capital

[20]Because all funding must come from debt or equity, imposing an adjustment cost on one is functionally very similar to imposing it on the other; holding all else equal, decreasing borrowing is only possible if dividends fall. However, modeling the cost through dividend adjustments has the benefit of tractability in the presence of both short- and long-term debt.

stock K^i_{t+1} valued at the investment good price p^I_t, net of debt B^i_{t+1}, times the recovery fraction ζ_t). [21]

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

$$\varphi(d^i_t) = d^i_t + \kappa \left(d^i_t - \bar{d^i} \right)^2. \tag{21}$$

Total dividend payouts, inclusive of adjustment costs, are therefore given by

$$\varphi(d^i_t) = p^i_t Y^i_t - p^I_t I^i_t - p^M_t MM^i_t - w_t L^i_t - B^i_t + \frac{B^i_{t+1}}{R_t}. \tag{22}$$

We assume that all firms face the same aggregate debt constraint parameter ζ_t and dividend adjustment cost κ, but allow for steady state dividend payouts $\bar{d^i}$ to vary across sectors.

[21] As in Jermann and Quadrini (2012), we interpret the one-period debt B_{t+1} as "long-term debt". This formulation provides a tractable way to distinguish longer-term unsecured borrowing from short-term debt (which is subject to collateral constraints). Extending to model allow for debt with longer maturities would complicate the firm's problem but would not meaningfully affect our results. We also follow their approach in assuming that the decision to default is made after revenues are realized and capital depreciates but before the intratemporal debt is repaid, which implies that the enforcement constraint (equation 20) will value the capital stock at current prices.

4.4 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 and intermediate inputs:

$$Y_t^M = \sum_i \left(IM_t^i + MM_t^i \right) + C_t^M \qquad \text{and} \qquad Y_t^N = \sum_i IN_t^i + C_t^N \tag{23}$$

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

$$\beta(1 + i_t) = (\beta(1 + i_{t-1}))^\rho \left(\pi_t^{\phi_\pi} \right)^{1-\rho} \exp(e_t^M). \tag{24}$$

Following Monacelli (2009), we ensure that the calibration results in the financial constraint binding in the steady state and then linearize around that steady state, assuming that it will continue to bind for small perturbations. [22]

4.5 Parameter Values

The model's parameter values are shown in table 6. Our goal with the model is to show that two simple mechanisms—financial frictions and an input-output production structure—interact to generate qualitatively realistic changes in the behavior of both real and financial variables in response to easing financial frictions without any bespoke calibration. To that end, we impose identical production functions in both sectors and use the same parameter values as Jermann and Quadrini (2012) whenever possible with the exception of those governing the degree of financial frictions, $\bar{\zeta}$ and κ, which we discuss in section 4.6. We set the persistence of shocks to the same values as in Jermann and Quadrini (2012), and set their variances to match the variance decomposition of employment from their model as closely as possible.[23]

Most other parameter values (such as coefficient on inflation in the Taylor rule) are

[22] Appendix section C.2 derives the full set of first-order and equilibrium conditions.
[23] See Appendix section C.1.

Table 6: Model parameter values

Parameter	Value	Description	Source/target
β	0.9825	Discount factor	Jermann and Quadrini (2012)
α	1.8834	Labor disutility	Jermann and Quadrini (2012)
δ	0.025	Capital depreciation rate	Jermann and Quadrini (2012)
$\bar{\zeta}$	0.1669	Steady state borrowing limit	Debt/GDP
κ_{pre}	0.1525	Dividend adjustment cost	IBD estimates
κ_{post}	0.03	Dividend adjustment cost	IBD estimates
τ	0.35	Tax rate	Jermann and Quadrini (2012)
θ	0.36	Capital share in production	Jermann and Quadrini (2012)
ρ	0.745	Interest rate persistence	Jermann and Quadrini (2012)
ϕ_π	2	Taylor rule coeff. on π_t	Standard
σ	0.28	Mfg share of consumption good	vom Lehn and Winberry (2022)
ψ	0.82	Mfg share of investment good	vom Lehn and Winberry (2022)
ν	0.19	Mfg materials share in production	vom Lehn and Winberry (2022)
ϕ^M, ϕ^N	10, 50	Price adjustment costs	Howes (2023)
ϵ	11	Consumption elasticity	10% steady state markup
ω	2	Investment adjustment cost	Howes (2023)
γ	3	Total labor supply elasticity	Standard
η	1	Sectoral labor elasticity	Horvath (2000)
χ	0.08	Mfg weight in labor aggregator	pre-1984 employment share

Notes: The parameters κ_{pre} and κ_{post} capture the degree of financial frictions before and after our financial deepening experiment. See section 4.6 for details.

common throughout the literature, and our results do not depend on any particular values; however, the shares of manufactured goods in the aggregates for consumption (σ) and investment (ψ), which are not present in the single-sector framework of Jermann and Quadrini (2012), are crucial for our results. These values determine manufacturing's role in producing durable investment goods; if $\psi > \sigma$, then manufacturing will be relatively more important for investment than consumption. We calibrate these parameters by aggregating the more granular industry values calculated in vom Lehn and Winberry (2022), who provide a detailed industry mapping of the consumption, investment, and production networks, to obtain $\sigma = 0.28$, $\psi = 0.82$, and $\nu = 0.19$. These values imply that the manufacturing sector produces roughly one quarter of the inputs to consumption goods, but more than three quarters of the inputs to investment goods.[24]

[24] $\sigma = 0.28$ is the average share of consumption goods produced by the manufacturing sector from 1947-2018. $\psi = 0.82$ is the share of all equipment investment produced by the manufacturing sector. $\nu = 0.19$

Another important parameter is manufacturing's weight in the labor aggregator (χ), which helps determine the manufacturing employment share. This is a key moment in our model because the change in *aggregate* employment volatility following financial deepening will depend in part on the size of the manufacturing sector. We calibrate this parameter to set the steady-state manufacturing share of employment to its pre-1984 average of 23.45 percent.

4.6 Financial Constraints and Volatility

To study 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 costs κ are large in each sector, and one in which they are small. We reduce financial frictions in each sector by the same amount since both manufacturing and nonmanufacturing firms had access to the potential benefits from financial deepening. All other aspects of the calibration—including the variances of all shocks—are identical across the two model simulations. We discipline this exercise based on our results from interstate banking deregulation from section 3. In particular, we choose $\kappa_{pre} = 0.1525$ and $\kappa_{post} = 0.03$, the same values in each sector, to generate a decline in employment volatility of 32.9 percent[25], which represents the fraction of the mean decline in employment volatility accounted for by interstate banking deregulation based on the point estimates

is the average share of material inputs to production coming from the manufacturing sector. Given our emphasis on durability as the key feature of investment, a natural extension would be to include a role for structures. If we instead calculate the durable share of investment as the portion of inputs to nonresidential fixed investment (which includes equipment, nonresidential structures, and intellectual property products like software) coming from the manufacturing or construction sectors, we obtain a similar value of $\psi = 0.74$. As a robustness check, we verify in Appendix B.2 that our employment growth volatility results are unchanged if we combine construction and manufacturing employment, although the lack of construction-specific income and balance sheet data prevent us from a similar exercise for financial volatility. Including the construction sector has no effect on the consumption share, as residential construction is not part of consumption expenditure in GDP accounting.

[25] Using the mean state-level manufacturing employment share of 17.48 percent, this implies a change of $0.223 - 0.064 \times 17.48 = -0.896$, which is 72.8 percent of the mean decline in the cyclicality of employment (1.23). We target a decline of 32.9 percent, which is 72.8 percent of the fundamental decline in table 2.

Table 7: Change in model variances with and without financial frictions.

Model Variable	Change in variance (percent)
Employment	-32.9
Debt	+3.9
Dividends	+66.8

from tables 4 and 5.[26]

Table 7 displays the changes in variance of key macro and financial variables in the model. As in our results above, the variance of 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.[27] Model impulse responses to a financial shock are displayed in figure 5. When financial frictions are high, adjustment costs deter firms from absorbing financial shocks solely through their balance sheets, and they 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 also repeat the variance decomposition exercises in sections 2.2 and 2.3 using simulated data. We 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 8 compares the empirical and model-based decomposition for employment, and table 9 does the same for financial ratios.

Although we set the values of κ to match exactly our estimated decline in employment volatility due to interstate banking deregulation, the resulting decompositions of volatility from reducing financial frictions are untargeted moments.[28] The declines in

[26]Following Jermann and Quadrini (2012), we set $\bar{\zeta}$ to match the debt to GDP ratio. If instead we take the values of $\bar{\zeta}$ and κ directly from Jermann and Quadrini (2012), turning dividend adjustment costs completely off results in nearly identical results.

[27]Recall that financial shocks in the model are captured by shocks to the fraction of collateral recoverable by lenders after default (ζ_t).

[28]In the model decomposition, sector sizes are the same with manufacturing making up 23.45% of total employment whether financial frictions are high or low, so there is no composition effect, and hence the total change is equal to the fundamental change.

Table 8: 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%**	***–32.9%***
Direct manufacturing effect (C^{VM})	**–14.1**	***–8.1***
Direct nonmanufacturing effect (C^{VN})	**–8.1**	***–6.8***
Total covariance effect (C^{Cov})	**–23.0**	***–18.1***
Approx manufacturing covariance effect (C_M^{Cov})	–16.4	*–13.0*
Approx nonmanufacturing covariance effect (C_N^{Cov})	–6.6	*–5.1*
Total manufacturing contribution ($C^{VM} + C_M^{Cov}$)	–30.5	*–21.1*
Total nonmanufacturing contribution ($C^{VN} + C_N^{Cov}$)	–14.7	*–11.8*
Total change in employment growth volatility (Δ^T)	**–51.4%**	***–32.9%***

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.

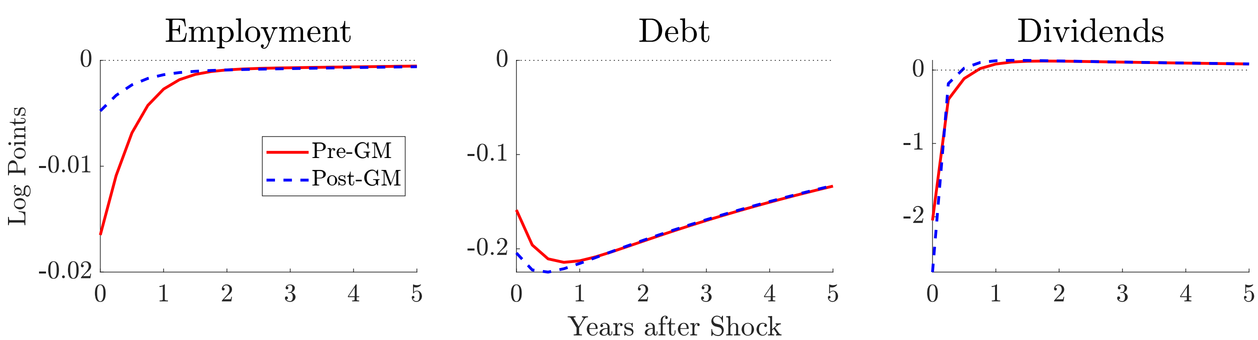

Figure 5: Impulse responses to a contractionary financial shock.

Notes: Pre-Great Moderation (red solid) has $\kappa = 0.1525$ for each sector; post-Great Moderation (blue dashed) has $\kappa = 0.03$ for each sector.

Table 9: 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%**	***+3.9%***	***+66.8%***
C^{VM}	+194.3	+848.0	*+1.5%*	*+20.9%*
C^{VN}	+16.1	+291.5	*+0.3%*	*+8.5%*
C^{Cov}	+154.6	+778.9	*+2.1%*	*+37.5%*
Δ^T	**+210.3%**	**+1,282.8**	***+3.9%***	***+66.8%***

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.

employment volatility within each sector closely match their empirical counterparts relative to the total fundamental decline: manufacturing volatility declines roughly by twice as much as nonmanufacturing volatility. In the model-based decomposition of total employment changes—the exact same exercise as in section 2.2—manufacturing accounts for 64.1% of the decline in employment volatility in the model, nearly the same as the 67.5% observed in the data. The breakdowns of the direct and covariance effects are also comparable. The fact that the manufacturing sector in the model, as in the data, is the primary driver of the reduction in volatility despite being smaller than the nonmanufacturing sector and being exposed to the exact same change in financial conditions points to its unique role in driving business cycles. We discuss this point in more detail in section 5 below.

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, as 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*.[29] 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 (more than three-quarters for both debt and dividends) than the nonmanufacturing sector.

5 Discussion

The previous section showed that easing financial constraints for all firms in our model can replicate both the aggregate and sector-specific changes in volatility observed during the Great Moderation. Here we highlight manufacturing firms' unique role as producers of long-lived investment goods as the primary mechanism driving our results. We conclude by discussing the implications of this channel for policymakers and regulators.

Changing financial frictions in our model affects its business cycle properties through two fundamental channels. The first channel governs the degree to which shocks originating entirely within the financial sector have real effects on output, employment, and investment. Without financial frictions, firms perfectly offset financial shocks by adjusting the composition of debt and equity and leave production and employment decisions unchanged. However, if firm balance sheets cannot costlessly absorb these shocks, nonfinancial variables will be forced to adjust instead. The second channel distorts the transmission of *other* shocks in the model; our results suggest that the effects of monetary policy shocks in particular increase with the severity financial frictions.

Investment goods play a key role in determining the importance of both channels. As in the data, manufacturing output in our model is disproportionately important in the

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

production of investment goods. Demand for these long-lived capital goods is more sensitive to financial shocks than demand for nondurable consumption 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 largely by adjusting the composition of debt and equity, rather than through 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.

To see this, figure 6 displays the responses to financial and monetary policy shocks of investment, debt, and dividends for both pre- and post-Great Moderation calibrations along with their counterparts from when we *only* reduce financial frictions for manufacturing firms. When we reduce frictions only on manufacturing firms, the increase in financial volatility is essentially the same as when we reduce frictions for both sectors, and the magnitude of the investment response to financial and monetary policy shocks is sharply attenuated. By contrast, if we reduce only frictions on nonmanufacturing firms, financial volatility is unchanged, and the investment response becomes larger. These results support the notion that reduction of financial frictions on manufacturing firms allows the economy to absorb financial and monetary policy shocks at least partially through balance-sheet adjustments rather than through changes in real investment.

Next, we use two counterfactuals to show that our results are dampened when we reduce the importance of investment goods in the overall economy. First, we increase the depreciation rate of capital by 25% so that investment goods have shorter productive lifespans. Next, we reduce capital's share in the production of final goods by 25%. The

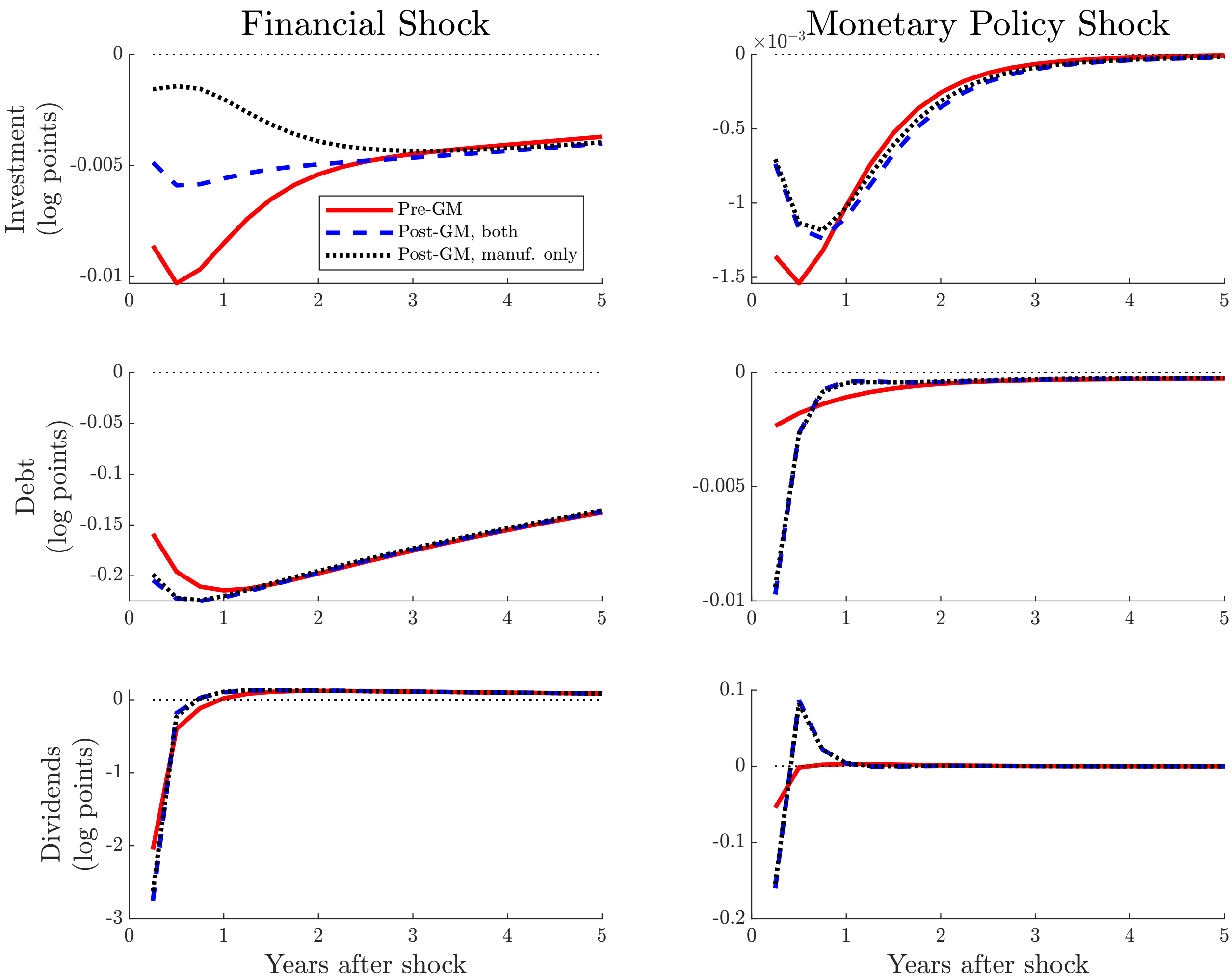

Figure 6: Impulse responses to contractionary financial and monetary policy shocks.

Notes: Pre-Great Moderation (red solid) has $\kappa = 0.1525$ for each sector; post-Great Moderation, both (blue dashed) has $\kappa = 0.03$ for each sector; post-Great Moderation, manuf. only (black dotted) has $\kappa = 0.03$ for manufacturing and $\kappa = 0.1525$ for nonmanufacturing.

effects on changes in volatility after financial deepening are summarized in table 10. Both changes dampen our results relative to the baseline: employment volatility declines by less, and financial volatility increases by less. Taken together, these results highlight the importance of interactions between real investment and financial frictions.

In our model, the only feature that distinguishes the manufacturing sector from the nonmanufacturing sector is its greater role in producing investment goods. What is special about these goods that drives their unique importance in determining firms' responses to changes in financial frictions? The key property that distinguishes investment

Table 10: Model experiments

Parameters:	Experiment: Baseline $\delta = 0.025$ $\theta = 0.36$	Higher Depreciation $\delta = 0.03125$ $\theta = 0.36$	Smaller Capital Share $\delta = 0.025$ $\theta = 0.27$
% change in volatility of			
Employment	–32.9%	–27.0%	–16.0%
Debt	+3.9%	+3.7%	+3.4%
Dividends	+66.8%	+68.8%	+63.3%

Notes: This table compares the changes in volatility from reducing financial frictions under three different parameterizations: the baseline calibration from section 4, one with a higher depreciation rate, and one with a smaller capital share in production. In each case, all other parameters are the same as in the baseline. See section 5 for details.

from other model variables is its long useful lifespan, which allows it to smooth shocks intertemporally. By investing more in response to an expansionary shock today, firms can avoid having to make large adjustments to other variables like employment after the shock fades. To the extent that financial frictions inhibit this substitution, however, this can cause larger adjustments in other variables like labor. Thus, by allowing firms to more efficiently absorb shocks using their balance sheets, easing financial frictions allows for smoother paths of investment and, therefore, employment.

6 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 interstate 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 analyze its 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 makes them highly responsive 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 three important takeaways for researchers and policymakers. The first concerns whether the effects of the 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 industries with prominent roles in the production of investment goods. A final implication of our results is that an economy's response to financial deepening can change depending on the composition of investment goods. To the extent that aggregate investment increasingly consists of intangible capital goods like software or intellectual property[30], future reductions in financial frictions will be more likely to affect aggregate volatility by impacting the behavior of the service sectors responsible for producing these goods.

[30] See Howes and von Ende-Becker (2022) for additional description of this phenomenon in the US and Bloesch and Weber (2021) for a discussion of the implications for monetary policy.

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Appendix

A Interstate Banking Deregulation

A.1 Deregulation dates by state

Table 11: 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.

A.2 Robustness checks

Here we we report three important robustness checks for our IBD results in section 3. In our baseline specification in Equation 7, we interacted the dummy for IBD treatment with $share^i$, which we defined as the state's manfuacturing employment share from 1977 (the last year in which no state had passed IBD legislation). We first report similar results under two alternative measures of employment share. In table 12, we instead use $preIBDshare^i$, which we define as the manufacturing employment share in state i in the year immediately preceding that state's passage of IBD legislation. Note that, because $preIBDshare^i$ will still be time-invariant for each state, its coefficient will again be perfectly collinear with the state fixed effects. The results are very similar in magnitude and significance to our main specification reported in table 5.

Table 12: Effects of pre-IBD employment shares on IBD transmission

	RGSP	Employment	Unemployment rate
IBD_t^i	1.143**	0.117	0.093
	(0.463)	(0.627)	(0.114)
$IBD_t^i \times preIBDshare^i$	-0.138***	-0.070*	-0.030***
	(0.034)	(0.037)	(0.009)
N	1334	1653	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 a modified version Equation 7. IBD_t^i is a dummy variable taking values of zero prior to a state implementing interstate banking deregulation and one after. $preIBDshare^i$ is the fraction of state i's total employment in the manufacturing sector in the year immediately preceding that state's passage of IBD legislation, and is not reported because it will be perfectly collinear with the state fixed effects. 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. Employment data come from BLS Current Employment Statistics.

Second, in table 13, we instead interact the IBD dummy with the manufacturing employment share in state i at time t. Unlike the specifications in tables 5 and 12, the coefficient on $mfgshare_t^i$ will be time-varying and thus not collinear with the state fixed effects. The fact that manufacturing is much more volatile than nonmanufacturing across many dimensions, it is unsurprising that these coefficients are positive. However, while the point estimate for the interaction term with employment becomes noisier, the interaction terms remain statistically significant and all of the magnitudes are extremely similar to our baseline results in table 5.

Table 13: Effects of time-varying employment shares on IBD transmission

	RGSP	Employment	Unemployment rate
IBD_t^i	0.578	-0.002	0.045
	(0.505)	(0.637)	(0.143)
$mfgshare_t^i$	0.197***	0.083	0.0231**
	(0.057)	(0.055)	(0.011)
$IBD_t^i \times mfgshareshare_t^i$	-0.102***	-0.061	-0.026**
	(0.036)	(0.039)	(0.011)
N	1334	1653	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 a modified version Equation 7. IBD_t^i is a dummy variable taking values of zero prior to a state implementing interstate banking deregulation and one after. $mfgshare_t^i$ is the fraction of state i's total employment in the manufacturing sector in year t. 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. Employment data come from BLS Current Employment Statistics.

Finally, we consider new estimators that account for treatment effect heterogeneity. Recent work including De Chaisemartin and d'Haultfoeuille (2020), Goodman-Bacon (2021), Sun and Abraham (2021), and Callaway and Sant'Anna (2021) has shown that the canonical two-way fixed effects approach with staggered treatment that we use to study the effects of IBD in section 3 can be biased in the presence of heterogeneous treatment effects. Here, we report qualitatively similar results using the estimator developed in De Chaisemartin and d'Haultfoeuille (2024) that accounts for these concerns.

Our approach here deviates slightly from equation 7 (and that of earlier work analyzing the empirical effects of IBD) by assuming that IBD provides a continuous "dose" of treatment whose size depends on a state's pre-IBD manufacturing employment share

($IBDshare_t^i = IBD_t^i \times share^i$). We report estimates using the `did_multiplegt_dyn` Stata package in table 14. These coefficients are somewhat smaller than the estimates from section 3, though the sign remains negative. The number of observations here is noticeably lower because these estimates exclude already-treated observations from the control groups.

Table 14: Robust estimates of the effects of employment shares on IBD transmission

	RGSP	Employment	Unemployment rate
$IBDshare_t^i$	-0.046**	-0.044	-0.016*
	(0.018)	(0.035)	(0.010)
Observations	251	251	251

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

Notes: This table shows the results of estimating Equation **??**. $IBDshare_t^i$ is the product of the post-IBD indicator variable and 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. Employment data come from BLS Current Employment Statistics.

B Variance decomposition details and extensions

B.1 Components of variance decomposition

Table 15: Employment growth variance decomposition

	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	

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 ω used in equation 3.

B.2 Employment decomposition including construction

Table 16: Total employment growth variance decomposition

Source	**Contribution**
Total changes from composition (Δ^C)	**–15.2%**
Total changes from fundamentals ($\Delta^F = C^{VD} + C^{VD} + C^{Cov}$)	**–44.3%**
Direct durable effect (C^{VD})	**–21.0**
Direct nondurable effect (C^{VN})	**–4.4**
Total covariance effect (C^{Cov})	**–18.9**
Approx. durable covariance effect (C_D^{Cov})	–16.4
Approx. nondurable covariance effect (C_N^{Cov})	–4.7
Total durable contribution ($C^{VM} + C_D^{Cov}$)	–37.4
Total nondurable contribution ($C^{VN} + C_N^{Cov}$)	–9.1
Total change in employment growth volatility (Δ^T)	**–52.8%**

Notes: This table shows a modified version of the decomposition from equations 3 for the combined manufacturing and construction ("durable") sectors. The top row reports the total change in volatility due to changing durable 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 durable sector (C^{VD}), nondurable sector (C^{VN}), and covariance effects (C^{Cov}). The table also provides an approximate allocation of the covariance contribution across durable and nondurable sectors. The bottom rows summarize the total durable and nondurable contributions, highlighting that changes specific to the durable sector (-37.4pp) accounted for the vast majority of the decline in total fundamental volatility (-44.3%). Note that the total change shown in the last row will not generally equal the value shown in table 2 because it is derived from a different approximation.

C Model appendix

C.1 Calibration of shock processes

When calibrating the persistence and variance for our shocks, we follow Jermann and Quadrini (2012) as closely as possible, but given the differences between our models—both in the structure of the economy and the types of shocks—it is not possible to follow them exactly. For those shocks that are in both models, we use their values for the persistence. We then calibrate the variances so that our pre-Great Moderation calibration matches the long-run variance decomposition of employment in their model, with our labor supply shock picking up the residual variance from their model. Importantly, the parameterization of these shocks is unchanged in any of the model experiments discussed in sections 4.6 and 5. These values are summarized in tables 17 and 18.

Table 17: Calibration of shock processes

Shock	Persistence	Standard Deviation
Total factor productivity	0.902	0.029
Financial	0.969	0.012
Monetary policy	0.203	0.005
Investment-specific technology	0.922	0.02
Labor supply (residual)	0.1	0.02

Notes: The source of the persistence values is Jermann and Quadrini (2012), while the standard deviations are set to match the variance decomposition of employment in their paper, with our labor supply shock picking up the residual variance.

Table 18: Employment's long-run variance decomposition

Shock	Jermann and Quadrini (2012)	Pre-GM calibration
Total factor productivity	19.4	20.55
Financial	33.5	37.03
Monetary policy	6.5	4.42
Investment-specific technology	5.1	6.5
Labor supply (residual)	35.5	31.5

Notes: Long-run variance of total hours due to model shocks. The last row is our residual labor supply shock, and the sum of all remaining shocks in Jermann and Quadrini (2012).

C.2 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 manufacturing sector (M) and one for the nonmanufacturing sector (N). mc_t^i is the marginal cost of production, mpl_t^i is the marginal product of labor, 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. All prices are normalized by the aggregate consumption good price index.

$$\frac{1}{C_t} = \lambda_t \tag{25}$$

$$p_t^M C_t^M = \sigma C_t \tag{26}$$

$$p^N C_t^N = (1-\sigma) C_t \tag{27}$$

$$\left(C_t^M\right)^{\sigma} \left(C_t^N\right)^{(1-\sigma)} = C_t \tag{28}$$

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

$$\lambda_t w_t^N = \alpha \left(1-\chi\right)^{\frac{-1}{\eta}} \left(L_t\right)^{\gamma - \frac{1}{\eta}} \left(L_t^N\right)^{\frac{1}{\eta}} \tag{30}$$

$$L_t = \left[\chi^{\frac{-1}{\eta}} \left(L_t^M\right)^{\frac{1+\eta}{\eta}} + \left(1-\chi\right)^{\frac{-1}{\eta}} \left(L_t^N\right)^{\frac{1+\eta}{\eta}}\right]^{\frac{\eta}{1+\eta}}. \tag{31}$$

$$\Lambda_t = \beta \mathbb{E}_t \left[\frac{\lambda_{t+1}}{\lambda_t}\right] \tag{32}$$

$$\mathbb{E}_t \left[\frac{\Lambda_t (1+i_t)}{\pi_{t+1}}\right] = 1 \tag{33}$$

$$(1+i_t) = \frac{R_t - \tau}{1-\tau} \tag{34}$$

$$P_t C_t + \frac{B_{t+1}}{(1+i_t)} = B_t + W_t^N L_t^N + W_t^M L_t^M + P_t d_t + P_t T_t \tag{35}$$

$$\left((1-\epsilon)p_t^i+(\epsilon)mc_t^i\right)-\phi^i\left(\pi_t^i-1\right)\pi_t^i+\phi^i\mathbb{E}_t\left[\Lambda_t\left(\frac{\varphi_{d,t}}{\varphi_{d,t+1}}\right)\left(\pi_{t+1}^i-1\right)\pi_{t+1}^i\left(\frac{Y_{t+1}^i}{Y_t^i}\right)\right]=0 \tag{36}$$

$$\beta(1+i_t)=(\beta(1+i_{t-1}))^{\rho}\left(\pi_t^{\phi_\pi}\right)^{1-\rho}\exp(e_t^M). \tag{37}$$

$$Y_t^i=A_tX_t^i\left(MM_t^i\right)^{\nu}\left(K_t^i\right)^{\theta}\left(L_t^i\right)^{1-\theta-\nu} \tag{38}$$

$$mpl_t^i=mc_t^i(1-\theta-\nu)A_tX_t^i(K_t^i)^{\theta}(L_t^i)^{-\theta-\nu}(MM_t^i)^{\nu} \tag{39}$$

$$mpk_t^i=mc_t^i\theta A_tX_t^i(K_t^i)^{\theta-1}(L_t^i)^{1-\theta-\nu}(MM_t^i)^{\nu} \tag{40}$$

$$w_t^i=mpl_t^i\left(1-\mu_t^i\phi_{d,t}^i\right) \tag{41}$$

$$p_t^M=mc_t^i\nu A_tX_t^i(L_t^i)^{1-\theta-\nu}(K_t^i)^{\theta}(MM_t^i)^{(\nu-1)}\left(1-\mu_t^i\varphi_{d,t}^i\right) \tag{42}$$

$$p_t^MIM_t^i=p_t^I\psi I_t^i \tag{43}$$

$$p_t^NIM_t^i=p_t^I(1-\psi)I_t^i \tag{44}$$

$$p_t^I=\left(\frac{p_t^M}{\psi}\right)^{\psi}\left(\frac{p_t^N}{1-\psi}\right)^{1-\psi} \tag{45}$$

$$\begin{aligned}p_t^I=mk_t^i\exp(v_t^i)&\left[\left(1-\frac{\omega}{2}\left(\frac{I_t^i}{I_{t-1}^i}-1\right)\right)^2-\omega\left(\frac{I_t^i}{I_{t-1}^i}-1\right)\left(\frac{I_t^i}{I_{t-1}^i}\right)\right]\\&+\mathbb{E}_t\left[\Lambda_t\left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i}\right)\exp(v_{t+1}^i)mk_{t+1}^i\omega\left(\frac{I_{t+1}^i}{I_t^i}-1\right)\left(\frac{I_{t+1}^i}{I_t^i}\right)^2\right]=0\end{aligned} \tag{46}$$

$$mk_t^i=\mathbb{E}_t\left[\Lambda_t\left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i}\right)\left[mk_{t+1}^i(1-\delta)+\left(1-\mu_{t+1}^i\varphi_{d,t+1}^i\right)mpk_{t+1}^i\right]\right]+p_t^I\zeta_t\mu_t^i\varphi_{d,t}^i \tag{47}$$

$$R_t\mathbb{E}_t\left[\Lambda_t\left(\frac{\varphi_{d,t}^i}{\varphi_{d,t+1}^i}\right)\right]+\zeta_t\mu_t^i\varphi_{d,t}^i\left(\frac{R_t}{1+i_t}\right)=1 \tag{48}$$

$$\varphi(d_t^i)=d_t^i-\kappa\left(d_t^i-\bar{d}^i\right)^2 \tag{49}$$

$$\varphi^i_{d,t} = 1 + 2\kappa \left(d^i_t - \bar{d}^i \right) \tag{50}$$

$$\zeta_t \left(p^I_t K^i_{t+1} - \frac{B^i_{t+1}}{1 + i_t} \right) = p^i_t Y^i_t \tag{51}$$

$$\varphi(d^i_t) = p^i_t Y^i_t - p^I_t I^i_t - p^M_t MM^i_t - w_t L^i_t - B^i_t + \frac{B^i_{t+1}}{R_t} \tag{52}$$

$$K^i_{t+1} = (1 - \delta) K^i_t + \exp(v^i_t) \left[1 - \frac{\omega}{2} \left(\frac{I^i_t}{I^i_{t-1}} - 1 \right)^2 \right] I^i_t \tag{53}$$

$$I_t = I^M_t + I^N_t \tag{54}$$

$$K_t = K^M_t + K^N_t \tag{55}$$

$$B_t = B^M_t + B^N_t \tag{56}$$

$$d_t = d^M_t + d^N_t \tag{57}$$

$$Y^D_t = \sum_i \left(ID^i_t + MM^i_t \right) + C^D_t, \quad Y^N_t = \sum_i \left(IN^i_t \right) + C^N_t \tag{58}$$

$$\pi^i_t = \left(\frac{p^i_t}{p^i_{t-1}} \right) \pi_t \tag{59}$$