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Abstract[1]

Financial inclusion is strikingly low in emerging economies. In only a few years, financial technologies (fintech) have led to a dramatic expansion in the number of non-traditional credit intermediaries, but the macroeconomic and credit-market implications of this rapid growth of fintech are not known. We build a model with a traditional banking system and endogenous fintech intermediary creation and find that greater fintech entry delivers positive long-term effects on aggregate output and consumption. However, greater entry bolsters aggregate firm financial inclusion only if it stems from lower barriers to accessing fintech credit by smaller, unbanked firms. Decreasing entry costs for fintech intermediaries alone has only marginal effects in the aggregate. While firms that adopt fintech credit are less sensitive to domestic financial shocks and contribute to a reduction in output volatility, greater fintech entry also leads to greater volatility in bank credit, thereby introducing a tradeoff between output volatility and credit-market volatility.

JEL classifications: E24, E32, E44, F41, G21
Keywords: Financial access and participation, Endogenous firm entry, Banking sector, Fintech entry, Emerging economy business cycles

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1 Introduction

It is well known that in emerging economies (EMEs), access to formal credit markets represents a significant barrier for firms (Beck and Demirgüç-Kunt, 2006; Beck, Demirgüç-Kunt, and Martínez Pería, 2007). As a result, compared to advanced economies, EMEs have much lower average shares of firms with bank credit—that is, lower firm participation in the domestic banking system or aggregate firm financial inclusion (Section 2; Epstein and Finkelstein Shapiro, 2021). Recent policy efforts aimed at promoting greater firm financial inclusion have taken place alongside growing levels of digital adoption by firms. Coupled with the advent of financial technologies (fintech), greater digital adoption has led to a dramatic expansion in the number of fintech intermediaries, albeit from low initial levels (see Section 2). The business model of these non-traditional financial intermediaries leverages the use of digital technologies to provide a variety of financial services—e.g., lending and credit provision via digital banks and matching-based platforms, digital savings and payments—with fewer barriers compared to traditional banks. Importantly, many fintech intermediaries cater to small firms, most of which are financially excluded or unbanked due to the high costs of participation in the traditional banking system.

Against this backdrop, the dramatic growth in the number of EME fintech intermediaries in recent years is seen as a promising avenue to increase competition in domestic credit markets—where traditional banks have played a dominant role—but also to bolster firms' access to credit (IFC, 2017; BIS, 2018, 2020; Sahay et al., 2020; Cantú and Ulloa, 2020). The policy impetus to reduce barriers to formal credit access is further bolstered by the fact that small firms account for a significant share of employment and job creation and make up the bulk of firms (Ayyagari, Demirgüç-Kunt, and Maksimovic, 2011; IFC, 2017). However, the implications of the sharp expansion in fintech intermediary entry for aggregate firm financial inclusion, the potential crowding out of resources in the traditional banking system, and the consequences for both credit market and macroeconomic volatility in EMEs are not known.

In this paper, we provide a quantitative assessment of these implications by building a framework with endogenous firm entry, a traditional banking system, and endogenous fintech-intermediary creation where firms differ in their sources of credit and the economy's degree of firm financial inclusion is endogenous.

Calibrating the model to match key facts on the extensive margin of firm financial inclusion, fintech intermediaries, and cyclical credit market dynamics in EMEs, we find that an increase in the number of fintech intermediaries that is commensurate with the annual growth rate of fintech intermediaries observed in recent years can have positive effects on long-term aggregate consumption and output. Our model suggests that these positive effects are driven by greater overall firm creation and improved firm-level outcomes among firms that start off being financially excluded but, as a result of greater fintech entry, are able to access fintech credit. However, the resulting reallocation of resources towards these firms leads to a reduction in aggregate bank credit. Notably, while greater fintech intermediary entry bolsters the overall number of firms with credit, it also brings about an increase in the total number of firms. Then, whether greater fintech intermediary entry is ultimately reflected in an increase in the share of firms with credit (irrespective of source)—a summary measure of aggregate firm financial inclusion—depends on the root cause of this greater entry. More specifically, greater fintech intermediary entry rooted in lower intermediary entry costs—that is, a supply-driven increase in entry—has no discernible impact on aggregate firm financial inclusion; in contrast, greater entry rooted in firms' lower barriers to accessing fintech credit—a demand-driven increase in fintech intermediary entry—bolsters aggregate firm financial inclusion significantly. This finding suggests that the large increase in fintech intermediary entry in EMEs need not have quantitatively meaningful positive effects on aggregate firm financial inclusion if greater fintech intermediary entry is rooted in lower entry costs for these intermediaries, and not in lower barriers to access to fintech credit by firms.

From a business cycle standpoint, greater fintech intermediary entry leads to a non trivial reduction in output volatility—a reduction that is driven by the more subdued response of firms that use fintech credit to domestic financial shocks, even as these firms represent a very small fraction of the universe of firms in the economy. In contrast, the response to shocks of firms that rely on bank credit remains virtually unchanged amid greater fintech intermediary entry. As a result, given the reduction in output volatility, greater fintech intermediary entry generates an increase in the relative volatility of bank credit and the relative volatility of consumption. More broadly, our findings suggest that greater fintech intermediary entry may introduce a tradeoff between greater relative volatility, gains in aggregate financial inclusion, and positive long run macro outcomes.

Our model, which focuses explicitly on the role of fintech in improving firms' credit market participation, features two firm categories—financially included and financially excluded—each with an endogenous measure of firms. Financially included firms—which embody large, formal EME firms—face higher entry costs and, upon entry, have access to a more productive technology and working capital loans from traditional monopolistically competitive banks at no additional cost. In contrast, financially excluded firms—which embody small, unbanked EME firms—face lower entry costs but initially enter with access to a less productive technology and no bank credit. To capture the fact that many fintech intermediaries in EMEs focus on catering to small, unbanked firms, we allow for a subset of these firms to access working capital loans financed by fintech intermediaries. Only those financially excluded firms that have high-enough productivity upon entry and incur an additional fixed cost—for example, the cost of digital adoption, which is a natural prerequisite for using fintech—ultimately use fintech credit. As such, the number of financially excluded firms that, via the usage of fintech credit, become financially included is endogenous. Finally, entry by fintech intermediaries is endogenous and subject to sunk entry costs, where these intermediaries compete for funding resources with traditional banks. This implies that the number of fintech intermediaries in the market shapes the equilibrium cost of fintech credit and, via competition for funding, can affect equilibrium bank credit.

Our paper is primarily related to the macro literature on endogenous firm entry, to growing work on the macroeconomic consequences of financial inclusion in developing and emerging economies, and to the macroeconomic implications of digital adoption in these economies. In particular, our model builds on the well known Bilbiie, Ghironi, and Melitz (2012) (BGM) endogenous firm entry framework. This model has been enriched along several dimensions, one of which is the inclusion of financial intermediation. The few studies that consider the interaction of firm dynamics with financial intermediation include Stebunovs (2008) and Cacciatore, Ghironi, and Stebunovs (2015), who analyze the macroeconomic consequences of changes in U.S. interstate banking competition, and Totzek (2011), who adapts the BGM environment to the banking system and characterizes the business cycle effects of oligopolistic bank entry in the United States. The way we model the entry of fintech intermediaries is closest to Totzek (2011). However, in contrast to his framework, which maintains a fixed set of firms, we explicitly incorporate endogenous firm entry and heterogeneous access to credit markets and sources—including fintech—which are at the heart of our model and analysis. In the context of EMEs, Barreto, Finkelstein Shapiro, and Nuguer (2021) study how domestic barriers to firm entry and their link to participation in the banking system shape the propagation of foreign banking-sector shocks in EMEs. Their work focuses solely on traditional banks and does not address the role of fintech intermediaries in shaping credit market dynamics.

On the financial inclusion front, Dabla-Norris, Ji, Townsend, and Unsal (2021) use a macro framework with heterogeneity in financing constraints and highlight how the interaction of these constraints and their relative incidence are critical for assessing the tradeoffs between financial inclusion, macroeconomic outcomes, and inequality in developing countries. Closer to our work, Epstein and Finkelstein Shapiro (2021) analyze the labor market and business cycle consequences of greater firm and household financial participation in EMEs in a model with equilibrium unemployment, endogenous firm entry, and heterogeneous and endogenous participation in domestic credit markets. They show that joint, as opposed to individual, improvements in firm and household financial participation are critical not only for lowering aggregate volatility in EMEs but also for generating business cycle dynamics that more closely resemble those of advanced economies. Building on their work, our framework also features two firm categories that differ in credit market participation, each with an endogenous measure of firms. There are two critical differences between their model and ours. First, Epstein and Finkelstein Shapiro (2021) focus solely on firm financial participation but abstract from modeling the banking system. In contrast, we explicitly introduce a formal credit structure with traditional banks and the creation of fintech intermediaries. Second, we allow financially excluded firms to endogenously become financially included by deciding to use fintech credit. These two distinct features are important as they allow us to explicitly characterize the implications of fintech-led firm financial inclusion as well as the potential impact of greater fintech intermediary entry on the domestic traditional banking system, including the implications for bank profits and bank credit volatility.

Turning to recent work on digital adoption and digital financial technologies in EMEs, Beck et al. (2018) analyze the macroeconomic effects of M-Pesa, Kenya's well known mobile money payment technology, in a framework where M-Pesa improves access to interfirm trade credit. They find that the use of this digital payment technology has large and positive output effects. In recent work, Ji, Teng, and Townsend (2021) use a spatial model with heterogeneous households to analyze the differential regional and distributional effects of bank expansion and digital banking in Thailand. Finally, Finkelstein Shapiro and Mandelman (2021) analyze the link between digital adoption by firms, the structure of labor markets, and labor market outcomes in developing countries in a framework with endogenous firm entry, a firm digital adoption margin, and self-employment. Their findings highlight the interaction between digital adoption and barriers to firm entry and how this interaction matters for understanding the labor market consequences of firm digital adoption and automation. Borrowing from this last paper, our model incorporates a costly digital adoption choice which, in our fintech-intermediary context, is a necessary condition for financially excluded firms to access fintech intermediaries and therefore credit markets.

Our contributions are threefold. First, we build a framework where the adoption of fintech credit by firms and the entry of fintech intermediaries are both endogenous. This feature, which is absent in existing models, allows us to explicitly characterize the most relevant supply and demand factors that shape the credit market and macroeconomic effects of the rapid expansion of fintech intermediaries in EMEs. This same feature is also essential to gain a deeper understanding of the macro-financial implications of fintech expansion. Second, we consider fintech entry in a context with firm heterogeneity in participation in domestic credit markets. This feature is crucial to understanding how fintech shapes overall firm financial inclusion in EMEs in the presence of a traditional banking system that has historically catered to a small segment of (mainly larger, formal) firms. Third, in contrast to existing studies on the macroeconomic effects of digital financial technologies, we not only analyze the average effects of fintech entry on long run aggregate outcomes, but also look at the cyclical credit market and macroeconomic implications. Understanding the effects of fintech entry on credit market dynamics and business cycles in EMEs is particularly relevant given the high pace at which fintech intermediation has expanded in a very short time span.

As such, our work provides a first step to shed light on these effects.

The rest of the paper is organized as follows. Section 2 presents recent facts on the role of small firms in total employment, digital adoption by firms, and the growing presence of fintech intermediaries in EMEs. Section 3 describes the model. Section 4 presents the quantitative analysis of the model. Section 5 concludes.

2 Financial Participation, Digital Adoption, and Fintech in EMEs

Given our interest in the business cycle and macro-financial implications of fintech entry, we focus on a group of EMEs that has been extensively studied in the EME business cycle literature. This group is comprised of Argentina, Brazil, Chile, Colombia, Malaysia, Mexico, Peru, Philippines, South Africa, Thailand, and Turkey. Another key advantage of focusing on this country group is that these economies have business-cycle frequency data on bank credit, which allows us to readily discipline the baseline volatility of credit in our model.

First, we highlight the prevalence of micro, small, and medium enterprises (MSMEs) in EMEs and their sizable contribution to total employment in order to stress their importance as a key source of employment and labor income. Second, we document the presence of a significant MSME finance gap—measured as the difference between potential loan demand by MSMEs and current MSME loan volumes (as a share of GDP)—for a large share of firms in EMEs. This finance gap suggests the presence of significant room for further domestic credit market development and deepening in these economies. Finally, using available data, we highlight the expansion of digital services and adoption—a necessary condition for using fintech—and summarize existing evidence on the rapid expansion of fintech intermediaries in EMEs in recent years.

Table 1: Firm Size Distribution, Finance Gap Ratios, and Firm Financial Participation in Emerging Economies

Country	**MSMEs (% of Formal Firms)**	**Formal Micro Firms (% of Formal MSMEs)**	**Empl. in Formal MSMEs (% of Formal Employment)**	**Formal MSME Finance Gap (% of GDP)**	**Potential Informal MSME Loan Demand (% of GDP)**	**Credit to Private Sector by Banks (% of GDP)**	**Formal Firms with a Bank Loan (% of Formal Firms)**	**Informal MSMEs (% of All MSMEs, 2010)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Argentina	98.0	71.0	49.8	14.7	5.1	15.4	42.4	81.0
Brazil	99.6	98.0	54.2	27.2	22.2	59.5	–	75.0
Chile	98.5	76.4	46.0	3.5	2.86	78.6	–	–
Colombia	99.7	94.0	–	13.2	10.5	49.8	62.4	69.8
Malaysia	98.5	77.0	–	7.2	13	117.1	31.9	84.6
Mexico	–	92.3	–	14.3	6.8	26.9	–	68.2
Peru	99.5	95.5	88.7	4.2	19.7	42.4	77.8	70.8
Philippines	99.6	91.0	63.3	76.0	–	45.6	29.9	84.6
South Africa	–	84.3	–	9.7	7.7	65.6	–	81.8
Thailand	99.7	7.9	79.5	10.3	36.1	112.1	15.5	87.2
Turkey	99.8	97.1	75.5	11.2	13.29	65.9	–	39.0
Average	**99.2**	**80.4**	**65.3**	**17.4**	**13.4**	**61.7**	**43.3**	**74.2**

Notes: Formal firms refer to firms registered with local or tax authorities. Informal firms are unregistered firms. Micro firms are defined as having less than 10 workers. The definition of Micro, Small, and Medium Enterprises (MSMEs) varies slightly by country but is generally defined as firms with less than 250 workers. The MSME Finance Gap is measured as the difference between potential loan demand by MSMEs and current MSME loan volumes as a share of GDP (see https://www.smefinanceforum.org/sites/default/files/Data%20Sites%20downloads/MSME%20Report.pdf for more details). The share of informal MSMEs is obtained using data from 2010 (the latest available year with data by formality status). Sources: IFC MSME Finance Gap Report 2019, IFC MSME Economic Indicators 2019, World Bank World Development Indicators, World Bank Enterprise Surveys, and IFC Enterprise Finance Gap 2010.

Firm Financial Participation and Formal Finance Gaps The International Finance Corporation's (IFC) MSME Economic Indicators Database provides the broadest and latest available data on the number of formal firms—firms that are officially registered with their country's local or tax authorities—by firm size for a host of EMEs. In turn, the IFC's MSME Finance Gap Report offers a comprehensive snapshot of the formal MSME finance gap across countries. While these data pertain to formal firms only, we stress that the large majority of firms in EMEs are informal and therefore lack access to formal credit markets (IFC, 2010, 2013; column 8 in Table 1).[2] As such, the facts on firm financial inclusion and formal credit usage we present below should be interpreted as an upper bound for the actual proportion of EME firms that participate in formal credit markets.

Table 1 shows that most formal firms in EMEs are categorized as MSMEs (column 1).[3] Moreover, the bulk of MSMEs are firms with less than 10 workers—that is, micro and small firms (column 2). Despite their small size, MSMEs still account for a significant share of total formal employment (column 3). Turning to firm credit among MSMEs, the average MSME finance gap as a share of GDP—for both formal and informal MSMEs—is sizable, especially when compared to current average bank credit-GDP ratios in these economies (columns 4, 5, and 6). To complement these facts, we use related data from the World Bank Enterprise Surveys (WBES) to stress the relatively low levels of firm participation in formal credit markets: on average, only 40 percent of formal firms in EMEs have a bank loan (column 7 in Table 1). The same survey data also shows that roughly 40 percent of formal firms report not needing a loan. However, this still leaves a significant and non-trivial share of firms that report needing bank loans but do not have access to bank credit. Of course, once we consider the fact that most MSMEs are informal (column 8), the already small share of formal firms with bank loans implies that only a very small fraction of the total universe of firms in EMEs participate in the banking system by using bank credit. More broadly,

[2] The latest IFC data on MSMEs by formality status is only available until 2010. Thus, column 8 in this table, which shows the share of informal MSMEs, is only meant to be illustrative of the breadth of firm informality in EMEs.

[3] Comparable data on the firm size distribution and access to credit across countries, especially EMEs, are notoriously difficult to obtain. As such, the facts in Table 1 are only meant to be illustrative of the fact that in EMEs, formal credit markets, especially for MSMEs, are substantially underdeveloped and participation in the domestic banking system tends to be limited for a large share of (primarily informal or unregistered) firms.

based on the data in columns 7 and 8, a simple back-of-the-envelope estimate of the total share of MSMEs that use bank credit *inclusive of informal MSMEs* is 10-15 percent of the universe of MSMEs.

To put the limited degree of firm financial participation above in perspective, consider the degree of firm financial participation in advanced economies. Similar to EMEs, existing evidence shows that MSMEs also account for the bulk of firms in advanced economies. Moreover, for firms that participate in formal credit markets, bank loans and credit lines are the primary sources of formal external financing. Indeed, data from the European Commission's Survey on the Access to Finance of Enterprises (SAFE) and from the IFC suggest that the average share of European MSMEs (inclusive of informal MSMEs) that use bank loans and credit lines is roughly 3 to 4 times larger than in EMEs. Taken together, the facts above make clear that there is significant room to bolster firm access to formal credit in EMEs, which is where digital adoption and the emergence of fintech come in.

Digital Adoption and Fintech Expansion Despite recent improvements in measuring digital adoption and fintech in EMEs, panel data on these measures are often scarce and yearly coverage varies by indicator. These limitations notwithstanding, Table 2 uses available panel data to provide a snapshot of the evolution of digital adoption and fintech in these economies in recent years. The table shows that firms have steadily adopted digital technologies. In addition, the share of individuals with mobile money accounts, while low, has been growing rapidly; and, in a very short time span, the shares of individuals who have adopted digital payments and who use the internet—both relevant for fintech access—have also grown non-trivially alongside mobile broadband subscriptions. Finally, the number of fintech firms, many of which provide lending platforms to individuals and firms, has grown dramatically in recent years.[4]

[4] According to the Cambridge Center for Alternative Finance (CCAF), several EMEs—Argentina, Brazil, Chile, Colombia, Malaysia, Mexico, and the Philippines—are part of the top 20 lower-middle and upper-middle income economies based on per capita alternative-finance volumes. Examples of fintech firms in EMEs that offer digital payments and/or banking services, several of which compete with traditional banks, include, among others, PagSeguro (Latin America); Creditas, Stone Co., and Nubank (Brazil); Fiserv (Brazil and Mexico); Sempli (Colombia), Credijusto and Konfio (Mexico); PrimeKeeper (Malaysia); Bank Zero and Jumo World Limited (South Africa); and Investree (Thailand) (Patwardhan, Singleton, and Schmitz, 2018; Sahay et al., 2020).

Table 2: Firm Digital Adoption, Digital Services' Access and Usage, and Fintech Firms in Emerging Economies

Country	**Firm Digital Adoption Index***		**Mobile Money Account (% Age 15+)***		**Made/Received Digital Payments in Past Year (% Age 15+)***		**Mobile Broadband Subscriptions Per 100 Individuals**		**Share of Individuals Using the the Internet**		**Number of Fintech Firms†**	
	2014	**2016**	**2014**	**2017**	**2014**	**2017**	**2017**	**2018**	**2017**	**2018**	**2017**	**2018**
Argentina	0.681	0.690	0	2	34	40	80.65	–	74.29	–	72	116
Brazil	0.646	0.678	1	5	50	58	90.87	88.11	67.47	70.43	230	380
Chile	0.771	0.816	4	19	53	65	86.26	91.58	82.33	–	–	84
Colombia	0.640	0.674	2	5	30	37	48.96	52.32	62.26	64.13	84	148
Malaysia	0.517	0.549	3	11	48	70	113.35	116.70	80.14	81.20	–	–
Mexico	0.585	0.626	3	6	29	32	65	69.97	63.85	65.77	180	273
Peru	0.594	0.608	0	3	22	34	65.66	–	50.45	55.05	16	57
Philippines	0.530	0.569	4	5	20	25	68.44	–	60.05	–	–	–
South Africa	0.653	0.690	14	19	59	60	69.61	77.49	56.17	–	–	–
Thailand	0.551	0.567	1	8	33	62	79.73	83.62	52.89	56.82	–	–
Turkey	0.640	0.680	1	16	48	64	70.20	74.20	64.68	71.04	–	–
Average	0.62	0.65	3	9	38.73	49.73	76.25	81.75	64.96	66.35	116.40	176.33
Percent Change	–	5.0	–	200	–	28.4	–	7.21	–	2.1	–	51.5

Sources: World Bank World Development Report 2016, World Bank Global Findex Database, IDB 2018, ITU-D ICT Statistics. Notes: The Firm Digital Adoption Index takes values between 0 and 1 and is based on 4 indicators (number of servers, download speeds, 3G coverage, and fraction of firms that have websites). * The Digital Adoption Index is only available for years 2014 and 2016, and data on mobile money accounts and digital payments is only available for years 2014 and 2017. † Time series data on the number of fintech firms is only available for 2017 and 2018.

For example, based on data from Latin American EMEs, the average number of fintech firms in the region grew by 50 percent between 2017 and 2018. For comparison with the traditional banking system, data from the IMF's Financial Access Survey suggests that the average number of traditional commercial banks in EMEs has remained virtually unchanged since 2005. As we describe below, the sharp expansion in the number of fintech firms has taken place alongside a dramatic rise in the volume of fintech credit (Sahay et al., 2020; CCAF 2020; Rau, 2021). Importantly, recent evidence on the composition of fintech credit in Latin America and East Asia and the Pacific suggests that roughly two thirds of fintech credit is allocated to firms (Sahay et al., 2020; Cantú and Ulloa, 2020), and firms tend to use fintech credit primarily as working capital and to finance their investment expenditures (Claessens et al., 2018).

Based on data availability, focusing on Latin American EMEs (Argentina, Brazil, Chile, Colombia, Mexico, and Peru) provides the best snapshot of the characteristics, evolution, and growth of fintech in EMEs. In particular, IDB (2018) documents that out of all the fintech firms in the region, half of them focus on lending and/or payments and almost 50 percent of fintech startups focus on unbanked and underserved small firms and consumers. Moreover, between 2017 and 2018, digital banks, the majority of which are domestic, have grown by more than 150 percent while fintech balance-sheet lending—that is, direct lending to customers by fintech platform entities—has grown by more than 80 percent. More broadly, Cantú and Ulloa (2020) document that between 2013 and 2018, fintech credit has grown at an average annual rate of more than 180 percent, with business lending generally representing the largest share of market volume. Importantly, the key drivers of greater fintech entry in the region are twofold: (1) the high costs that individuals and firms face in order to access and use the services offered by the traditional banking system, and (2) the low rates of formal financial participation.[5] Finally, we note that while the latest data on digital adoption and fintech trends in EMEs are only available until 2018, the COVID-19 pandemic has only accelerated the pace of digital adoption in several EMEs (Apedo-Amah et al., 2020; CCAF,

[5] The adoption and use of fintech services is tightly connected to the share of the digitally-active population. For example, in 2017, 76 percent of the digitally-active population in Colombia used fintech services, with the corresponding shares in Peru, Mexico, Argentina, Chile, and Brazil being 75, 72, 67, 66, and 64 percent, respectively.

World Bank, and World Economic Forum, 2020).

In the next section, we present a framework with an endogenous extensive margin of firm participation in formal credit markets, traditional banks that cater to a subset of firms, and endogenous fintech intermediary entry. We then use the model to characterize the cyclical macro-financial and long term aggregate consequences of greater fintech entry in EMEs.

3 The Model

The small open economy (SOE) is comprised of households, firms, a monopolistically competitive traditional banking system, and monopolistically competitive fintech intermediaries. Traditional banks and fintech intermediaries represent the supply side of formal credit markets.[6]

Total output is produced by two categories of firms—financially included (i) and excluded (e)—each of which has an endogenous number of firms—a necessary feature to analyze endogenous changes in aggregate firm financial inclusion. Firms use labor to produce and face sunk entry costs in the spirit of Bilbiie, Ghironi, and Melitz (2012) (BGM) (as noted in BGM, the costly creation of new firms can be interpreted as a form of real investment akin to physical capital accumulation). The two categories of firms differ fundamentally in: (1) their initial barriers to entry; (2) their production technology upon entry; and (3) their participation (or lack thereof) in the traditional banking system via bank credit usage. We assume that i firms face higher entry costs, but incurring these costs allows firms to access credit from traditional banks and a high-productivity technology. Bank credit is used to finance a portion of i firms' wage bill (working capital) and the sunk costs associated with i-firm creation (a form of investment). In contrast, e firms face lower entry costs, enter the market without access to traditional banks or credit—that is, they are initially unbanked—and start off with a low-productivity technology. In this sense, i firms represent larger,

[6]To analyze the role of fintech intermediaries in shaping formal credit markets and short and long run macroeconomic outcomes in a transparent way, we abstract from modeling interfirm (input-based) trade credit, which is a relevant source of informal external finance for many firms, especially micro and small firms, in EMEs (IFC, 2010). Modeling interfirm trade credit for a subset of firms (those without access to bank credit) would introduce an additional layer of complexity without altering the main mechanisms of the model. In recent work, Suri et al. (2021) find that, in the context of Kenya, fintech-based digital loans did not replace other forms of existing credit.

formal firms in EMEs, which empirically account for the bulk of bank credit and tend to have better production technologies, while e firms represent micro and small firms, which empirically face high barriers to participating in the banking system and tend to use more precarious production technologies.

Even though e firms enter the market without being able to access to the traditional banking system, depending on their realized idiosyncratic productivity upon entry, some e firms are able to obtain loans offered by fintech intermediaries—fintech credit for short—and upgrade their technology, but only after incurring a fixed cost associated with access to fintech. Fintech credit is used to finance a portion of these firms' wage bill and the fixed cost they must incur to access fintech credit. This fixed cost can embody a number of factors, including the cost of digital technology adoption (a requirement to access fintech intermediaries) and the cost associated with upgrading production technology, among others, and as such can be considered a type of investment.[7] Only a segment of e firms—those with high-enough productivity upon entry—ultimately decide to use fintech credit and join the ranks of the financially included. This occurs endogenously (for more on the link between usage of digital financial services and productivity, see Beck et al., 2018).

As a baseline, we abstract from bank entry or exit. However, the entry of fintech intermediaries is endogenous and subject to sunk costs—a necessary ingredient to analyze fintech intermediary entry.[8] While fintech intermediaries tend to rely on a variety of funding sources—household deposits, venture capital, and/or equity issuance—given our interest in firm financial inclusion, we focus exclusively on fintech credit for firms as the sole service provided. We also assume that funds supplied by households are the sole source of funds for

[7]Other barriers to the use of fintech intermediaries beyond the cost of adopting digital technologies include, for example, the need for financial literacy and the state of public digital infrastructure (Sahay et al., 2020). The fixed cost in our framework is ultimately meant to embody any factors that contribute to the cost of accessing fintech credit.

[8]Traditional banks have also adopted digital technologies amid the expansion of firm digital adoption in EMEs. However, the main motive behind the adoption of these technologies is often to cater to existing clients and keep their client base, rather than to reach unbanked potential clients. It is possible that traditional banks can partner with fintech intermediaries to expand their market, or outright create their own fintech subsidiaries (these subsidiaries can be separate entities in order to segment the market for loans between clients that already have bank credit and new, unbanked clients). To the extent that the entry of fintech intermediaries is primarily rooted in the use of digital technologies to reach unbanked potential clients, the creation of fintech subsidiaries by traditional banks would be captured by the fintech-intermediary creation margin in our framework.

fintech intermediaries, though these funds can be interpreted more broadly as any external funding used by fintech intermediaries to finance their operations. Finally, aggregate productivity, foreign interest rate shocks, and domestic financial shocks, where the latter allow us to replicate important features of credit market dynamics in EMEs, drive business cycle fluctuations.

3.1 Production Structure

The description of the production structure—where two categories of firms differ in their access to formal credit—builds on Epstein and Finkelstein Shapiro (2021) and uses similar notation. Our setup differs from theirs by assuming frictionless labor markets and by enriching the formal credit market structure in two ways. First, we introduce banks that cater to i firms. Second, we introduce endogenous entry of fintech intermediaries, which cater to an endogenous subcategory of e firms.

3.1.1 Aggregate Output

A perfectly competitive output aggregator maximizes profits $\Pi_{a,t} = [P_t Y_t - P_{i,t} Y_{i,t} - P_{e,t} Y_{e,t}]$ subject to aggregate output $Y_t = \left[\alpha_y^{\frac{1}{\phi_y}} \left(Y_{i,t}\right)^{\frac{\phi_y - 1}{\phi_y}} + (1-\alpha_y)^{\frac{1}{\phi_y}} \left(Y_{e,t}\right)^{\frac{\phi_y - 1}{\phi_y}} \right]^{\frac{\phi_y}{\phi_y - 1}}$, where $\phi_y > 0$ and $0 < \alpha_y < 1$. $Y_{i,t}$ is the total output of i firms, $Y_{e,t}$ is the total output of e firms, and $P_{i,t}$ and $P_{e,t}$ are the respective nominal prices. Profit maximization delivers standard demand functions for each output category: $Y_{i,t} = \alpha_y \left(p_{i,t}\right)^{-\phi_y} Y_t$ and $Y_{e,t} = (1-\alpha_y) \left(p_{e,t}\right)^{-\phi_y} Y_t$, where $p_{i,t} \equiv P_{i,t}/P_t$ and $p_{e,t} \equiv P_{e,t}/P_t$ are relative firm-category prices.

3.1.2 Output by Firm Category

An incumbent firm ω_h in category $h \in \{e, i\}$ produces a single differentiated output variety within its own category, where $y_{h,t}(\omega_h)$ denotes firm ω_h's output. Total output in each category is given by $Y_{h,t} = \left(\int_{\omega_h \in \Omega_h} y_{h,t}(\omega_h)^{\frac{\varepsilon - 1}{\varepsilon}} d\omega_h \right)^{\frac{\varepsilon}{\varepsilon - 1}}$ where Ω_h is the potential measure of firms in category h and ε dictates the elasticity of substitution between firms' output within each category. It is straightforward to show that the demand for a given firm ω_h's output is given by

$$y_{h,t}(\omega_h) = \left(\frac{\rho_{h,t}(\omega_h)}{p_{h,t}}\right)^{-\varepsilon} Y_{h,t}, \tag{1}$$

for $h \in \{e, i\}$, where $p_{h,t} = \left(\int_{\omega_h \in \Omega_h} \rho_{h,t}(\omega_h)^{1-\varepsilon} d\omega_h\right)^{\frac{1}{1-\varepsilon}}$ and $\rho_{h,t}(\omega_h)$ is the relative price of firm ω_h's output. In what follows, we describe the problem of incumbent firms and delegate the description of the decisions on firm creation to the household's problem in Section 3.3.

3.1.3 Incumbent i Firms and Evolution of i Firms

Each new entrant into category i must incur the sunk entry (resource) cost $\psi_i > 0$. An incumbent firm ω_i uses labor $l_{i,t}(\omega_i)$ to produce output $y_{i,t}(\omega_i) = z_{i,t} l_{i,t}(\omega_i)$ where $z_{i,t}$ denotes the exogenous productivity that is common across firms in category i. Each period, firm ω_i obtains working-capital loans from banks to cover a fraction $0 \le \kappa_i \le 1$ of its wage bill in advance at a gross real interest rate $R^b_{l,t}$, with the bank loan being repaid at the end of the same period. Thus, from firm ω_i's perspective, the bank loan amount is $x_{b,t}(\omega_i) = \kappa_i w_{i,t} l_{i,t}(\omega_i)$ where $w_{i,t}$ is the real wage. Firm ω_i's profits in period t are therefore given by

$$\pi_{i,t}(\omega_i) = \rho_{i,t}(\omega_i) y_{i,t}(\omega_i) - w_{i,t} l_{i,t}(\omega_i) + x_{b,t}(\omega_i) - R^b_{l,t} x_{b,t}(\omega_i).$$

Formally, firm ω_i maximizes the expected present discount value of its profits $\mathbb{E}_t \sum_{s=t}^{\infty} \Xi_{s|t}[(1-\delta)^{s-t} \pi_{i,s}(\omega_i)]$ subject to its demand function $y_{i,s}(\omega_i) = (\rho_{i,s}(\omega_i)/p_{i,s})^{-\varepsilon} Y_{i,s}$, where $0 < \delta < 1$ is the exogenous probability that the firm exits the market at the end of each period and $\Xi_{s|t}$ is the household's stochastic discount factor between period s and t for $s \ge t$. It is easy to show that firm ω_i's optimal relative price is $\rho_{i,t}(\omega_i) = \left(\frac{\varepsilon}{\varepsilon-1}\right) mc_{i,t}$, where $mc_{i,t} = \left(1 - \kappa_i + \kappa_i R^b_{l,t}\right) w_{i,t}/z_{i,t}$ is the real marginal cost and $\varepsilon/(\varepsilon - 1)$ is the markup.

Denoting by $N_{i,t}$ the mass of active i firms and by $H_{i,t}$ the mass of new entrants to category i in period t, the evolution of i firms is given by $N_{i,t} = (1-\delta)\left(N_{i,t-1} + H_{i,t-1}\right)$, where we follow the timing convention in BGM and assume a one-period lag between entry and production.

3.1.4 Incumbent e Firms, Fintech Credit Adoption, and Evolution of e Firms

Each new entrant into category e must incur a sunk entry (resource) cost $\psi_e > 0$ where we assume that $\psi_e \leq \psi_i$. To introduce endogenous decisions on fintech credit usage, we assume that upon entry, each firm draws its idiosyncratic productivity a_e from a distribution $G(a_e)$ with support $[a_{\min}, \infty)$, where a_e remains unchanged until the firm exits the market with exogenous probability $0 < \delta < 1$. Given that each firm produces a single differentiated output variety ω_e within its own category, for ease of notation, a firm ω_e with idiosyncratic productivity a_e is denoted simply as firm a_e.

With this in mind, an e firm that enters the market and does not access fintech credit uses labor $l^n_{e,t}(a_e)$ and produces $y^n_{e,t}(a_e) = z^n_{e,t} a_e l^n_{e,t}(a_e)$ where $z^n_{e,t}$ denotes the common exogenous productivity of those e firms that do not participate in formal credit markets. In turn, an e firm that enters the market and adopts fintech credit uses labor $l^f_{e,t}(a_e)$ and produces $y^f_{e,t}(a_e) = z^f_{e,t} a_e l^f_{e,t}(a_e)$, where $z^f_{e,t}$ denotes the exogenous common productivity of e firms that use fintech credit, where $z^n_e < z^f_e$. As such, all else equal, firms that use fintech credit have greater productivity (via a more productive technology) compared to those that do not participate in credit markets (see Beck et al., 2018, for more on this assumption). Even though $z^f_{e,t}$ and $z^n_{e,t}$ are exogenous, e firms still have an endogenous idiosyncratic productivity component that will ultimately determine how many firms choose to use fintech credit.

Firm Profits and Fintech Credit Adoption If a firm's idiosyncratic productivity level a_e is below an endogenously determined threshold $\overline{a}_{e,t}$, the firm does not participate in credit markets and its individual profits are given by

$$\pi^n_{e,t}(a_e) = \rho^n_{e,t}(a_e) y^n_{e,t}(a_e) - w_{e,t} l^n_{e,t}(a_e),$$

where $\rho^n_{e,t}(a_e)$ is the firm's relative price and $w_{e,t}$ is the real wage of e firms. If instead $a_e \geq \overline{a}_{e,t}$, the firm incurs a fixed (resource cost) $\psi_a > 0$, which grants the firm access to working-capital loans from fintech intermediaries (this cost can represent, among other things, the fixed cost of digital adoption in order to access fintech credit). This firm's individual profits are given by

$$\pi^f_{e,t}(a_e) = \rho^f_{e,t}(a_e) y^f_{e,t}(a_e) - w_{e,t} l^f_{e,t}(a_e) - R^f_{l,t} x_{f,t}(a_e) + x_{f,t}(a_e) - \psi_a,$$

where $\rho^f_{e,t}(a_e)$ is the firm's relative price. $x_{f,t}(a_e)$ represents the firm's period-t working-capital loan from fintech intermediaries, which the firm uses to cover a fraction $0 \leq \kappa_e \leq 1$ of the firm's wage bill and the fixed resource cost ψ_a at a gross real interest rate $R^f_{l,t}$, where the fintech loan is repaid at the end of the period. Thus, from firm a_e's perspective, the fintech loan amount is $x_{f,t}(a_e) = \kappa_e \left(w_{e,t} l^f_{e,t}(a_e) + \psi_a \right)$. Given the above conditions, it follows that an e firm is indifferent between not participating in credit markets and obtaining fintech credit when $\pi^n_{e,t}(\overline{a}_{e,t}) = \pi^f_{e,t}(\overline{a}_{e,t})$. This condition implicitly pins down the idiosyncratic productivity threshold level $\overline{a}_{e,t}$ above which an e firm decides to use fintech credit.

Optimal Pricing Following similar steps to those of i firms, the optimal relative prices of e firms' individual output are given by $\rho^n_{e,t}(a_e) = \left(\frac{\varepsilon}{\varepsilon-1}\right) \frac{mc^n_{e,t}}{a_e}$ and $\rho^f_{e,t}(a_e) = \left(\frac{\varepsilon}{\varepsilon-1}\right) \frac{mc^f_{e,t}}{a_e}$, where $mc^n_{e,t} = w_{e,t}/z^n_{e,t}$ and $mc^f_{e,t} = \left(1 - \kappa_e + \kappa_e R^f_{l,t}\right) w_{e,t}/z^f_{e,t}$ are the respective real marginal costs of e firms that do not participate in credit markets and those that use fintech credit.

Evolution of e Firms Denoting by $N_{e,t}$ the mass of active e firms and by $H_{e,t}$ the mass of new entrants to category e in period t, the evolution of e firms is given by $N_{e,t} = (1-\delta)\left(N_{e,t-1} + H_{e,t-1}\right)$. Of note, given the idiosyncratic productivity threshold level $\overline{a}_{e,t}$, we can separate e firms into those that do not participate in credit markets, $N^n_{e,t} = G(\overline{a}_{e,t}) N_{e,t}$, and those that do via fintech credit, $N^f_{e,t} = \left[1 - G(\overline{a}_{e,t})\right] N_{e,t}$.

Firm Averages in Category e Given the presence of two subcategories of e firms, we can define two average idiosyncratic productivity levels, one for each subcategory. In particular, the average idiosyncratic productivity of e firms that do not participate in credit markets is $\widetilde{a}^n_{e,t} = \left[\frac{1}{G(\overline{a}_{e,t})} \int_{a_{min}}^{\overline{a}_{e,t}} a_e^{\varepsilon-1} dG(a_e)\right]^{\frac{1}{\varepsilon-1}}$. In turn, the average idiosyncratic productivity of e firms that use fintech credit is $\widetilde{a}^f_{e,t} = \left[\frac{1}{1-G(\overline{a}_{e,t})} \int_{\overline{a}_{e,t}}^{\infty} a_e^{\varepsilon-1} dG(a_e)\right]^{\frac{1}{\varepsilon-1}}$. We can then define average profits, average relative prices, and average output for the two subcategories of e firms as follows: $\widetilde{\pi}^n_{e,t} \equiv \pi^n_{e,t}(\widetilde{a}^n_{e,t})$ and $\widetilde{\pi}^f_{e,t} \equiv \pi^f_{e,t}(\widetilde{a}^f_{e,t})$, $\widetilde{\rho}^n_{e,t} \equiv \rho^n_{e,t}(\widetilde{a}^n_{e,t})$ and $\widetilde{\rho}^f_{e,t} \equiv \rho^f_{e,t}(\widetilde{a}^f_{e,t})$, and

$\widetilde{y}^n_{e,t} \equiv y^n_{e,t}(\widetilde{a}^n_{e,t})$ and $\widetilde{y}^f_{e,t} \equiv y^f_{e,t}(\widetilde{a}^f_{e,t})$. Finally, anticipating households' firm creation decisions in Section 3.3, we define average e-firm profits as $\pi_{e,t} = \left(\frac{N^n_{e,t}}{N_{e,t}}\right)\widetilde{\pi}^n_{e,t} + \left(\frac{N^f_{e,t}}{N_{e,t}}\right)\widetilde{\pi}^f_{e,t}$.

3.2 Financial Intermediation

There are two categories of financial intermediaries: traditional banks and fintech intermediaries. Both categories operate in a monopolistically competitive environment in the loan market and in a perfectly competitive environment in the deposit/funding market. Credit markets are segmented, with banks providing loans only to i firms and fintech intermediaries providing loans only to a subset of e firms (recall Section 2). Given our focus on fintech entry, the creation of fintech intermediaries is endogenous and subject to sunk entry costs while the measure of banks is fixed.[9]

3.2.1 Banks

There is a fixed measure of monopolistically competitive banks indexed by j over the $[0, B]$ interval with $B > 0$. Each bank j relies on household deposits $d_{b,t}(j)$ to finance loans to i firms.

The demand function for loans $x_{b,t}(j)$ of an individual bank j can be generally expressed as $x_{b,t}(j) = X_{b,t}\partial R^b_{l,t}/\partial r^b_{l,t}(j)$ where $X_{b,t}$ denotes the total amount of bank loans to i firms, $r^b_{l,t}(j)$ is the real gross lending rate offered by bank j, and $R^b_{l,t}$ is the average real gross lending rate in the banking system. Each bank j sets its gross real lending rate $r^b_{l,t}(j)$ to maximize profits $\pi_{b,t}(j) = r^b_{l,t}(j,)x_{b,t}(j) - R^b_{d,t}d_{b,t}(j)$, where $R^b_{d,t}$ is the common gross real deposit rate across banks, subject to the balance sheet constraint $x_{b,t}(j) = d_{b,t}(j)$ and bank j's demand for loans $x_{b,t}(j) = X_{b,t}\partial R^b_{l,t}/\partial r^b_{l,t}(j)$. Bank j's first-order conditions deliver the following standard optimal lending-deposit spread:

$$r^b_{l,t}(j) = \mu_{b,t}R^b_{d,t}, \tag{2}$$

where $\mu_{b,t}$ is the markup over the gross real deposit rate in the banking system. Under Dixit-

[9] Appendix A.2.6 presents results for a version of the baseline model where bank entry is also endogenous and shows that our main findings remain unchanged.

Stiglitz loan aggregation, the demand for bank loans is $x_{b,t}(j) = \left(r^b_{l,t}(j)/R^b_{l,t}\right)^{-\varepsilon_{b,t}} X_{b,t}$ and the markup $\mu_{b,t} = \varepsilon_{b,t}/\left(\varepsilon_{b,t} - 1\right)$ where $\varepsilon_{b,t} > 1$ is the elasticity of substitution between bank loans. We follow Gerali et al. (2010) and assume that $\varepsilon_{b,t}$ is subject to shocks. These shocks generate exogenous fluctuations in bank lending spreads and can therefore be interpreted as domestic financial shocks from the vantage point of banks and firms.

3.2.2 Fintech Intermediaries

Following an adaptation of BGM to financial intermediaries, there is an endogenous measure of monopolistically competitive fintech intermediaries indexed by $\zeta \in Z$ where Z is the potential measure of fintech intermediaries. Entry into the fintech credit market entails a sunk entry (resource cost) $\psi_f > 0$ (for example, the cost can represent the cost of setting up the necessary physical and digital infrastructure to offer digital financial services). Fintech intermediaries use funds supplied by households to finance loans to the subset of e firms that can access fintech credit. In what follows, we describe the problem of incumbent fintech intermediaries and address the decision on fintech intermediary creation as part of the household's problem.

Incumbent Fintech Intermediaries There is a basket of total fintech loans $X_{f,t}$ defined over the potential measure of fintech intermediaries Z. The demand for loans of an individual fintech intermediary ζ can be generally expressed as $x_{f,t}(\zeta) = X_{f,t}\partial R^f_{l,t}/\partial r^f_{l,t}(\zeta)$, where $r^f_{l,t}(\zeta)$ is the real gross lending rate offered by fintech intermediary ζ, and $R^f_{l,t}$ is the average real gross lending rate in the fintech sector. An active fintech intermediary ζ has individual profits $\pi_{f,t}(\zeta) = r^f_{l,t}(\zeta)x_{f,t}(\zeta) - R^f_{d,t}d_{f,t}(\zeta)$, where $R^f_{d,t}$ is the common gross real rate on household funds $d_{f,t}(\zeta)$, and a balance sheet constraint given by $x_{f,t}(\zeta) = d_{f,t}(\zeta)$.

Each fintech intermediary ζ chooses $r^f_{l,t}(\zeta)$ to maximize $\pi_{f,t}(\zeta)$ subject to its balance sheet constraint and its loan demand function $x_{f,t}(\zeta) = X_{f,t}\partial R^f_{l,t}/\partial r^f_{l,t}(\zeta)$. Taking first-order conditions, we obtain the following lending-deposit spread:

$$r^f_{l,t}(\zeta) = \mu_{f,t} R^f_{d,t}, \tag{3}$$

where $\mu_{f,t}$ is the markup over the (common) gross real deposit rate offered by fintech intermediaries. Under Dixit-Stiglitz aggregation, the demand for fintech loans is $x_{f,t}(\zeta) = \left(r^f_{l,t}(\zeta)/R^f_{l,t}\right)^{-\varepsilon_{f,t}} X_{f,t}$ where $\mu_{f,t} = \varepsilon_{f,t}/\left(\varepsilon_{f,t} - 1\right)$ is the lending markup and $\varepsilon_{f,t} > 1$ is the elasticity of substitution between fintech loans. Similar to traditional banks, we assume that $\varepsilon_{f,t}$ is subject to shocks that generate exogenous fluctuations in fintech lending spreads and can be similarly interpreted as domestic financial shocks.

Evolution of Fintech Intermediaries Denoting by $N_{f,t}$ the mass of active fintech intermediaries and by $H_{f,t}$ the mass of new fintech entrants in period t, the evolution of fintech intermediaries is given by $N_{f,t} = (1 - \delta_f)\left(N_{f,t-1} + H_{f,t-1}\right)$, where $0 < \delta_f < 1$ is the exogenous probability that a fintech intermediary exits the credit market.

3.3 Households, Firm Creation, and Fintech Creation

A representative household is the ultimate owner of firms, banks, and fintech intermediaries. The household consumes, supplies labor to firms in each firm category, supplies funds to banks and to fintech intermediaries, and makes decisions on the creation of i firms, e firms, and fintech intermediaries, taking all prices and individual profits as given.

Formally, the household chooses real consumption c_t,total labor supply to i firms $L_{i,t}$,total labor supply to e firms $L_{e,t}$, total real deposits to banks $D_{b,t}$ and total real funds channeled to fintech intermediaries $D_{f,t}$, foreign debt D^*_t, the desired number of i and e firms $N_{i,t+1}$ and $N_{e,t+1}$, the number of new firms in each category, $H_{i,t}$ and $H_{e,t}$, to achieve those targets, and both the desired number of fintech intermediaries $N_{f,t+1}$ and the number of new fintech entrants $H_{f,t}$ to maximize $\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t, L_{i,t}, L_{e,t})$ subject to the budget constraint

$$c_t + D_{b,t} + D_{f,t} + \left(1 - \kappa_i + \kappa_i R^b_{l,t}\right) \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_f H_{f,t} + D^*_t + \frac{\eta^*}{2}(D^*_t)^2 = w_{i,t} L_{i,t} + w_{e,t} L_{e,t}$$
$$+ R^b_{d,t-1} D_{b,t-1} + R^f_{d,t-1} D_{f,t-1} + S_{t-1} R^*_{t-1} D^*_{t-1} + \pi_{i,t} N_{i,t} + \pi_{e,t} N_{e,t} + \pi_{f,t} N_{f,t} + \pi_{b,t} B,$$

the evolution of i firms

$$N_{i,t+1} = (1 - \delta)(N_{i,t} + H_{i,t}), \tag{4}$$

the evolution of e firms

$$N_{e,t+1} = (1-\delta)(N_{e,t} + H_{e,t}), \tag{5}$$

and the evolution of fintech intermediaries

$$N_{f,t+1} = (1-\delta_f)(N_{f,t} + H_{f,t}), \tag{6}$$

where $u(c_t, L_{i,t}, L_{e,t})$ exhibits standard properties with respect to consumption and each category of labor. The terms $D_{b,t} = \int_0^1 b_{b,t}(j)dj$ and $D_{f,t} = \int_{\zeta \in Z} d_{f,t}(\zeta)d\zeta$, and $R^b_{d,t-1}$ and $R^f_{d,t-1}$ represent the average real gross bank deposit and fintech-intermediary fund rates, respectively. Recalling that firm creation is a form of investment and that a fraction $0 < \kappa_i < 1$ of the cost of i-firm creation is financed with bank credit at a gross real lending rate $R^b_{l,t}$, the term $\left(1-\kappa_i+\kappa_i R^b_{l,t}\right)\psi_i H_{i,t}$ represents the total resource cost of creating i firms. $(\eta^*/2)\left(D^*_t\right)^2$ is a quadratic debt adjustment cost function where $\eta^* > 0$ (see, for example, Cacciatore, Duval, Fiori, and Ghironi, 2016), R^*_t is the gross real foreign interest rate, and S_t is the country spread (Neumeyer and Perri, 2005). Average e-firm profits $\pi_{e,t}$ were defined in Section 3.1.4, and $\pi_{i,t}$, $\pi_{b,t}$, and $\pi_{f,t}$ denote average individual profits of i firms, banks, and fintech intermediaries, respectively.[10] The household's first-order conditions deliver standard Euler equations on bank deposits and fintech funds, $1 = \mathbb{E}_t \Xi_{t+1|t} R^b_{d,t}$ and $1 = \mathbb{E}_t \Xi_{t+1|t} R^f_{d,t}$, a standard Euler equation over foreign debt, $1 = \mathbb{E}_t \Xi_{t+1|t} S_t R^*_t + \eta^*(D^*_t)$, two standard labor supply conditions, $-u_{L_e,t} = w_{e,t}u_{c,t}$ and $-u_{L_i,t} = w_{i,t}u_{c,t}$, a firm creation condition for each firm category e and i

$$\psi_e = (1-\delta)\mathbb{E}_t \Xi_{t+1|t}\left[\pi_{e,t+1} + \psi_e\right], \tag{7}$$

and

$$\psi_i\left(1-\kappa_i+\kappa_i R^b_{l,t}\right) = (1-\delta)\mathbb{E}_t \Xi_{t+1|t}\left[\pi_{i,t+1} + \psi_i\left(1-\kappa_i+\kappa_i R^b_{l,t+1}\right)\right], \tag{8}$$

[10] Given the relatively new nature of fintech, it is possible that supplying funds to financial intermediaries could entail additional costs (for example, costs associated with monitoring) that may differ between types of financial intermediaries. Introducing such costs generates a steady-state differential between $R^b_{d,t}$ and $R^f_{d,t}$ but does not change any of our main conclusions.

and a fintech intermediary creation condition

$$\psi_f = (1 - \delta_f)\mathbb{E}_t \Xi_{t+1|t} \left[\pi_{f,t+1} + \psi_f \right], \tag{9}$$

where $\Xi_{t+1|t} \equiv \beta u_{c,t+1}/u_{c,t}$. The intuition behind the Euler equations for bank deposits and fintech funds and optimal labor supply is standard. The firm creation conditions equate, for each firm category, the marginal cost of creating an additional firm, given by the sunk entry cost, to the expected marginal benefit of doing so, where the latter is given by the expected value of average individual-firm profits and the continuation value if the firm remains in the market next period. In the case of i-firm creation, the marginal cost of firm creation takes into account the use of bank credit to cover part of the sunk entry cost of i firms. The fintech intermediary creation condition similarly equates the marginal cost of creating an additional fintech intermediary, given by the sunk entry cost, to the expected marginal benefit, where the latter is given by the expected value of average fintech intermediary profits and the continuation value if the fintech intermediary remains in the market next period.

3.4 Symmetric Equilibrium and Market Clearing

Following the macro literature on endogenous firm entry, we consider a symmetric equilibrium. This implies the following equilibrium relationships in credit markets:

$$r^f_{l,t} = N_{f,t}^{\frac{1}{\varepsilon_f - 1}} R^f_{l,t}, \tag{10}$$

$$X_{f,t} = N_{f,t}^{\frac{\varepsilon_f}{\varepsilon_f - 1}} x_{f,t}, \tag{11}$$

$$r^b_{l,t} = B^{\frac{1}{\varepsilon_b - 1}} R^b_{l,t}, \tag{12}$$

$$X_{b,t} = B^{\frac{\varepsilon_b}{\varepsilon_b - 1}} x_{b,t}, \tag{13}$$

where aggregate credit is defined as $X_t \equiv X_{b,t} + X_{f,t}$. In turn, goods-market clearing implies that

$$Y_{i,t} = N_{i,t}^{\frac{\varepsilon}{\varepsilon - 1}} y_{i,t}, \tag{14}$$

and

$$Y_{e,t} = \left(N_{e,t}^{n} \left(\widetilde{y}_{e,t}^{n} \right)^{\frac{\varepsilon-1}{\varepsilon}} + N_{e,t}^{f} \left(\widetilde{y}_{e,t}^{f} \right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{15}$$

where $y_{i,t}$, $\widetilde{y}_{e,t}^{n} = z_{e,t}^{n}\widetilde{a}_{e,t}^{n}l_{e,t}^{n}$ and $\widetilde{y}_{e,t}^{f} = z_{e,t}^{f}\widetilde{a}_{e,t}^{f}l_{e,t}^{f}$ represent average individual-firm output in category i and the two subcategories of e firms, respectively. Market clearing in labor markets implies that

$$L_{i,t} = l_{i,t}N_{i,t}, \tag{16}$$

and

$$L_{e,t} = N_{e,t}^{n}l_{e,t}^{n} + N_{e,t}^{f}l_{e,t}^{f}. \tag{17}$$

Market clearing in credit markets implies $X_{b,t} = D_{b,t} = \kappa_i \left(w_{i,t}L_{i,t} + \psi_i H_{i,t} \right)$ and $X_{f,t} = D_{f,t} = \kappa_e \left(w_{e,t}l_{e,t}^{f} + \psi_a \right) N_{e,t}^{f}$. Finally, the economy's resource constraint is given by

$$Y_t = c_t + \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_f H_{f,t} + \psi_a N_{e,t}^{f} + S_{t-1}R_{t-1}^{*}D_{t-1}^{*} + D_t^{*} + \frac{\eta^{*}}{2}(D_t^{*})^2, \tag{18}$$

where the trade balance is given by $tb_t = Y_t - \left(c_t + \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_f H_{f,t} + \psi_a N_{e,t}^{f} \right)$. For future reference, we define real investment as $inv_t \equiv \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_a N_{e,t}^{f}$ and the total number of firms as $N_t \equiv N_{e,t} + N_{i,t}$. Section A.1 of the Appendix presents the full list of equilibrium conditions.

4 Quantitative Analysis

As is well known from BGM, the presence of "love for variety" is an inherent component of macro models with endogenous firm entry, but this component is absent in empirical measurements of the CPI. In order to correctly compare model variables to their empirical counterparts, we need to adjust any real variable in the model—call this non-adjusted, model-based real variable $o_{na,t}$—to remove this variety effect. Following Cacciatore, Duval, Fiori, and Ghironi (2016), the model-based real variable $o_{m,t} = \Theta_t^{\frac{1}{1-\phi_y}} o_{na,t}$ where $\Theta_t = \left(\alpha_y N_{i,t}^{\frac{1-\phi_y}{1-\varepsilon}} + (1-\alpha_y) N_{e,t}^{\frac{1-\phi_y}{1-\varepsilon}} \right)$ is readily comparable to its counterpart in the data. In what follows, all model-based real variables are expressed in data-consistent terms (that is, as $o_{m,t}$) unless otherwise noted.

4.1 Calibration of Benchmark Economy

Functional Forms and Shocks Section 3 above presented several of the functional forms we adopt. The only functional forms that remain to be specified are the household's utility and the distribution of idiosyncratic productivity of e firms. We adopt Jaimovich-Rebelo preferences so that $u(c_t, L_{i,t}, L_{e,t}) = \frac{\left(c_t - Q_t\left(\gamma\frac{L_{e,t}^{1+\eta_e}}{1+\eta_e} + \gamma\frac{L_{i,t}^{1+\eta_i}}{1+\eta_i}\right)\right)^{1-\sigma} - 1}{1-\sigma}$ where $\sigma, \gamma, \eta_e, \eta_i > 0$ and $Q_t = c_t^{\gamma_c} Q_{t-1}^{1-\gamma_c}$, where $0 \leq \gamma_c \leq 1$ dictates the strength of the wealth effect on labor supply in the short run (Jaimovich and Rebelo, 2009). Following Ghironi and Melitz (2005), we assume a Pareto distribution for $G(a_e) = 1 - \left(\frac{a_{min}}{a_e}\right)^{k_p}$ with shape parameter $k_p > \varepsilon - 1$. This functional form implies that the average idiosyncratic productivity levels for each subcategory of e firms can be written as $\widetilde{a}_{e,t}^n = \widetilde{a}_{e,t}^f \left(\frac{\overline{a}_{e,t}^{k_p-(\varepsilon-1)} - a_{min}^{k_p-(\varepsilon-1)}}{\overline{a}_{e,t}^{k_p} - a_{min}^{k_p}}\right)^{\frac{1}{\varepsilon-1}} a_{min}$ and $\widetilde{a}_{e,t}^f = \left(\frac{k_p}{k_p-(\varepsilon-1)}\right)^{\frac{1}{\varepsilon-1}} \overline{a}_{e,t}$.

For the purposes of analyzing business cycle fluctuations amid financial shocks, we follow related literature and introduce convex adjustment costs in the number of firms and fintech intermediaries that do not affect the steady state (for similar costs associated with the adjustment of capital and loans in a context with financial shocks, see, for example, Iacoviello, 2015). In particular, we assume that in addition to paying sunk costs ψ_e and ψ_f for each new firm and fintech intermediary, respectively, households incur additional resource costs $\phi_h\left(H_{e,t}/H_e - 1\right)^{\xi_e}$, $\phi_h\left(H_{i,t}/H_i - 1\right)^{\xi_i}$, and $\phi_h\left(H_{f,t}/H_f - 1\right)^{\xi_f}$ where $\xi_e, \xi_i, \xi_f > 1$, $\phi_h > 0$, and variables without time subscripts denote those same variables in steady state.

Following the EME literature, business cycles are driven by aggregate productivity shocks and foreign interest rate shocks, as well as domestic financial shocks. We assume that sectoral productivities $z_{e,t}^n$, $z_{e,t}^f$, and $z_{i,t}$ follow AR(1) processes in logs with common persistence parameter $0 < \rho_z < 1$ and common (aggregate) shock $\nu_t^z \sim N(0, \sigma_z)$. Similarly, the elasticities of substitution associated with banks and fintech intermediaries, $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$, also follow AR(1) processes in logs with common persistence parameter $0 < \rho_\varepsilon < 1$ and common shock $\nu_t^\varepsilon \sim N(0, \sigma_\varepsilon)$. Therefore, in this context, ν_t^ε can be interpreted as an aggregate (that is, not bank- or fintech intermediary-specific) domestic financial shock that affects average lending spreads. Following Neumeyer and Perri (2005) and related studies, we assume that the country spread is inversely related to expected aggregate productivity, $S_t = -\eta_s \mathbb{E}_t[\mathbb{Z}_{t+1}]$, where parameter $\eta_s \geq 0$ dictates the strength of this inverse relationship and $\mathbb{Z}_t$ represents the aggregate component of sectoral productivities $z^n_{e,t}$, $z^f_{e,t}$, and $z_{i,t}$. The inclusion of country spreads allows us to discipline the model's cyclical dynamics on the trade-balance front. Finally, the gross real foreign interest rate follows an AR(1) process in logs with persistence parameter $0 < \rho_{R^*} < 1$ and shock $\nu^{R^*}_t \sim N(0, \sigma_{R^*})$.

Parameters from Literature A time period is a quarter. Following the EME business cycle literature and the macro literature on endogenous firm entry, we set $\beta = 0.985$, $\sigma = 2$, $\delta = 0.025$, and $a_{min} = 1$. We set $\gamma_c = 0.10$, which is consistent with the strength of the wealth effect in the short run in other EME studies (see, for example, Li, 2011). Choosing $\varepsilon = 4$ generates average markups consistent with those of EMEs (Díez, Leigh, and Tambunlertchai, 2018). As a baseline, we assume $k_p = 4.2$, which satisfies the condition $k_p > \varepsilon - 1$, and $\phi_y = 5$, which allows for relatively high substitutability between i and e output in total output. Based on data from the World Bank Enterprise Surveys (WBES), the proportion of working capital and investment among small firms that is financed with formal credit in our EME sample is 34 percent, so we set $\kappa_e = 0.34$. We assume quadratic adjustment costs in the creation of firms and fintech intermediaries in order to generate plausible investment dynamics so that $\xi_i = \xi_e = \xi_f = 2$ (for similar parameter-value assumptions in a model with financial frictions, see Iacoviello, 2015). Setting $\eta_e = \eta_i = 1.50$ delivers a Frisch elasticity of labor supply within the range in the literature. Since we are primarily interested in the consequences of fintech intermediary entry, we set the fixed measure of banks to $B = 1$ without loss of generality. Based on evidence from IDB (2018) and Cantú and Ulloa (2020), the average annual exit rate of fintech intermediaries is roughly 12 percent, so that $\delta_f = 0.03$. We normalize $z^n_e = 1$ and set $\rho_z = \rho_\varepsilon = 0.95$, and $\sigma_z = 0.01$. Finally, we set $\rho_{R^*} = 0.77$ and $\sigma_{R^*} = 0.0072$, which follows from estimating an AR(1) process for the real gross 3-month U.S. Treasury yield over the period 1990Q1-2018Q4.

Calibrated Parameters As a baseline and absent evidence suggesting otherwise, we assume that $\varepsilon_b = \varepsilon_f$. Moreover, we assume that in the baseline economy's steady state *only*, firms with credit (whether from banks or fintech intermediaries) have the same labor productivity. To understand what the resulting calibration target is, recall that e firms have both an endogenous productivity component reflected in steady-state $\widetilde{a}_e^f$ and an exogenous component reflected in z_e^f. Thus, the calibration target consistent with our assumption is $z_i = \widetilde{a}_e^f z_e^f$ (robustness checks confirm that this baseline assumption is innocuous and does not drive our main findings).

With these assumptions in mind, we calibrate parameters $\alpha_y, \varepsilon_b, \gamma, \kappa_i, \psi_e, \psi_i, \psi_a, \psi_f, \eta^*, z_e^f$, and z_i to match a set of first-moment targets based on available data for our EME sample. These targets are: an average ratio of bank credit to GDP of 50 percent (consistent with the average ratio in our EME sample from 2000 to 2018 per BIS data); an average lending-deposit spread of 8.5 percent (consistent with average quarterly spreads in our EME sample from 2000 to 2018 per IMF IFS data); a ratio of total i-firm output in total output of 65 percent (consistent with the average value added of large firms in total value added per available data from the OECD for select EMEs); a cost of creating an i firm equivalent to 8.6 percent of per capita GDP (consistent with the average cost of creating a business in our EME sample per World Bank Enterprise Survey data); average total hours worked representing one third of the household's time endowment (a standard target in the business cycle literature); an average share of firms with (bank and fintech) credit of 20 percent of the total measure of firms (consistent with IFC data inclusive of the presence of informal, and therefore financially excluded, firms); an average lending-rate differential between fintech intermediaries and banks of 5 percentage points (consistent with available evidence for EMEs from Claessens et al., 2018); an average share of e firms with fintech credit of 5 percent of the total measure of e firms (consistent with the average share of individuals with mobile money accounts adjusted by the average share of firm credit in total fintech credit in our EME sample); an average foreign debt-GDP ratio of 50 percent (consistent with World Bank data for our EME sample); a share of i labor in total labor of 0.55 (consistent with the average share of employment in large firms per available OECD data); and the calibration target linking z_i and z_e^f in the baseline steady state only.

Finally, we calibrate the parameters that directly shape the economy's cyclical dynamics, σ_ε, η_s, and ϕ_h, to match the following second moments: an average relative volatility of bank credit to the non-financial sector of 2.42 percent; a contemporaneous correlation between the trade balance-GDP ratio and GDP of -0.27; and an average relative volatility of real investment of 3.17 percent, per BIS and IMF IFS data for our EME sample spanning the period 2000Q1-2018Q4. Matching the relative volatilities of bank credit and investment allows us to replicate the cyclical behavior of domestic credit markets in EMEs in the baseline model, which is important for analyzing how fintech intermediary entry may quantitatively affect bank credit and total credit dynamics.

All told, we obtain the following parameter values: $\alpha_y = 0.5683, \varepsilon_b = \varepsilon_f = 12.9439, \gamma = 36.39, \kappa_i = 0.9287, \psi_e = 0.0389, \psi_i = 0.404, \psi_a = 0.0045, \psi_f = 0.6349$, $\eta^* = 0.0056, \eta_s = 0.10$, $z_e^f = 1.50, z_i = 4.6475$, $\sigma_\varepsilon = 0.364$, and $\phi_h = 0.0913$. Of note, the resulting values of z_e^f and z_i are such that firms with credit have greater productivity than those without credit, which is in line with existing evidence on the link between access to credit and productivity (see, for example, Dabla-Norris, Ho, and Kyobe, 2016).

4.2 Impact of Greater Fintech Intermediary Entry

We consider two individual experiments to shed light on the macroeconomic and macro-financial implications of greater fintech intermediary entry. First, we analyze a reduction in the sunk entry cost of fintech intermediaries, ψ_f. This reduction encourages greater fintech intermediary entry and leads to an increase in the average (or steady-state) measure of fintech intermediaries, N_f. Second, we analyze a reduction in the fixed cost that e firms incur to access fintech credit, ψ_a. This reduction in the fixed cost increases the demand for fintech credit by expanding the number of e firms that use such credit, which encourages the entry of fintech intermediaries. To discipline these experiments, in each case, we reduce the corresponding cost (ψ_f or ψ_a) so as to generate a 52-percent increase in the steady state measure of fintech intermediaries, holding all other parameters at their baseline values. Per Table 2 in Section 2, this percent increase matches the growth in the number of fintech intermediaries between 2017 and 2018 in EMEs.

4.2.1 Steady State Changes

Table 3 shows the steady state of select variables in the baseline economy ("Baseline Economy," column (1)), in a version of the economy with greater fintech intermediary entry obtained via a lower ψ_f ("Greater Fintech Intermediary Entry via Lower ψ_f," column (2)), and in a version of the economy with greater fintech intermediary entry obtained via a lower ψ_a ("Greater Fintech Intermediary Entry via Lower ψ_a," column (4)). The table also summarizes the resulting quantitative changes in the two experiments (column (3) for the reduction in ψ_f and column (5) for the reduction in ψ_a).[11]

In both experiments, the steady state expansion in the measure of fintech intermediaries N_f leads an increase in fintech credit X_f and to a reduction in average fintech lending rates R_l^f (of note, the reduction in R_l^f, in turn, reduces fintech lending spreads since the gross real return on fintech funds R_d^f, which depends solely on the household's subjective discount factor in steady state, remains unchanged).

[11]It is possible that ψ_f and ψ_a could be correlated (for example, if both costs are related to the cost of adopting digital technologies in the economy, a reduction in such cost would affect both fintech intermediaries and e firms considering the use of fintech credit). Our baseline analysis abstracts from this link between costs to highlight, separately, the supply and demand factors in the fintech credit market in a transparent way.

Table 3: Steady State Changes in Response to Greater Fintech Intermediary Entry (via Reduction in ψ_f or Reduction in ψ_a)

Variable	**Baseline Economy**	**Greater Fintech Intermediary Entry via Lower ψ_f**	**Change Relative to Baseline Economy (% or PP)**	**Greater Fintech Intermediary Entry via Lower ψ_a**	**Change Relative to Baseline Economy (% or PP)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of Fintech Intermediaries N_f	0.588	0.894	52%	0.894	52%
Aggregate Output Y	0.924	0.929	**0.48%**	0.955	**3.33%**
Aggregate Consumption c	0.778	0.781	**0.42%**	0.800	**2.89%**
e-Firm Wage w_e	1.746	1.760	**0.80%**	1.822	**4.39%**
i-Firm Wage w_i	2.107	2.099	**-0.37%**	2.029	**-3.68%**
Measure of e Firms N_e	223.445	228.601	**2.31%**	274.648	**22.91%**
Measure of e Firms with Fintech Credit N_e^f	11.172	12.138	**8.65%**	51.217	**358.43%**
Measure of i Firms N_i	41.896	41.979	**0.20%**	42.069	**0.41%**
Aggregate Fintech Credit X_f	0.057	0.060	**5.93%**	0.084	**47.98%**
Aggregate Bank Credit X_b	0.462	0.460	**-0.48%**	0.436	**-5.56%**
Aggregate Credit X	0.519	0.520	**0.23%**	0.521	**0.30%**
Share of e Firms with Fintech Credit N_e^f/N_e	0.050*	0.053	**0.31 PP**	0.187	**13.65 PP**
Share of Firms with Credit $\left(N_i + N_e^f\right)/N$	0.200*	0.200	0.001 PP	0.295	**9.45 PP**
Ave. Fintech Lending Spread $\left(R_l^f - R_d^f\right)$	0.135	0.095	**-3.96 PP**	0.095	**-3.96 PP**

Notes: $N \equiv (N_e + N_i)$ is the total measure of firms in the economy. All real variables are expressed in data-consistent terms unless otherwise noted. All numbers are rounded to three decimal places. **PP denotes Percentage Points**. An * denotes a targeted first moment. Percent and percentage-point changes in **blue** represent beneficial changes relative to the benchmark economy. Percent and percentage-point changes in **red** represent adverse changes relative to the benchmark economy.

Recall that the marginal cost of e firms that use fintech credit is $mc_e^f = \frac{\left(1-\kappa_e+\kappa_e R_l^f\right)w_e}{z_e^f \widetilde{a}_e^f}$ in steady state. Therefore, all else equal, the reduction in fintech lending rates puts downward pressure on the marginal cost of these firms, which leads to greater e-firm creation (reflected in a greater N_e), to an increase in the measure of e firms that use fintech credit (reflected in a greater N_e^f), to an increase in e labor (not shown), and to an increase in aggregate fintech credit (reflected in a greater X_f). The expansion in the number of fintech intermediaries also results in higher real e wages and in a small reduction in real i wages, which contributes to a reduction in average wage differentials between firm categories. We note that the quantitative reduction in i wages hinges heavily on the degree of substitutability between i and e output in total output, ϕ_y: a lower degree of substitutability would imply a marginal increase in real i wages. Regardless of the value of ϕ_y, though, greater fintech intermediary entry reduces wage differentials by bolstering e wages relative to i wages. Importantly, the increase in the measure of e firms that use fintech credit and the resulting increase in real e wages and e labor bolster household income, a portion of which is devoted to additional creation of i firms (reflected in a greater N_i). Since i firms use bank credit to finance a portion of their wage bill and the creation of i firms, the greater creation of additional i firms all else equal increases the demand for bank credit, but this is offset by the equilibrium reduction in firms' wage bill via lower i wages, ultimately resulting in a reduction in bank credit (reflected in a lower X_b).

From an aggregate standpoint, the overall amount of credit in the economy (that is, the sum of bank credit and fintech credit, X), consumption c, and output Y are all greater in an economy with a larger measure of fintech intermediaries, irrespective of the factor that induces the increase in intermediaries. These positive aggregate effects are in line with the positive output effects from mobile payment technologies that Beck et al. (2018) find in the context of Kenya's M-Pesa technology. A distinct feature of our analysis is its focus on how fintech intermediary entry affects not only macroeconomic outcomes, but also the traditional banking sector, firm creation across categories, and aggregate firm financial inclusion. Our interest in the traditional banking sector is relevant since banks account for the bulk of total credit and tend to cater to more productive firms.

Table 3 shows two additional and important results. First, the increase in fintech intermediary entry leads to an increase in the measure of both i firms and e firms, as well as an increase in the measure of e firms with fintech credit. Whether this translates into a greater share of firms with credit regardless of source, $\left(N_i + N_e^f\right)/N$, and therefore greater aggregate firm financial inclusion depends heavily on the quantitative change in the measure of e firms that use fintech credit. When greater fintech intermediary entry is rooted in a reduction in its sunk entry cost, the share $\left(N_i + N_e^f\right)/N$ remains for all intents and purposes unchanged relative to its baseline of 20 percent. In other words, the dramatic expansion in fintech intermediary entry has no quantitatively meaningful impact on aggregate firm financial inclusion.[12] In contrast, when greater fintech intermediary entry is demand-driven and rooted in e firms finding easier to access fintech credit, the share $\left(N_i + N_e^f\right)/N$ expands by almost 10 percentage points. Moreover, for the same increase in the measure of fintech intermediaries, a reduction in e firms' barriers to accessing fintech credit has quantitatively-larger positive effects on macro aggregates. This larger effect is driven by the larger increase in the total number of firms in the economy.

4.2.2 Cyclical Volatility and Dynamics

Main Results Table 4 compares unconditional volatilities in the benchmark economy (column (1)) and in the economy under greater fintech intermediary entry for the same two scenarios (greater entry rooted in lower ψ_f (column (2)) or lower ψ_a (column (4)) and their respective comparisons with the benchmark economy (columns (3) and (5))) .[13] A greater average measure of fintech intermediaries reduces the volatility of output ($\sigma_{Y,t}$), the relative volatility of labor and real wages among e firms ($\sigma_{L_e,t}/\sigma_{Y,t}$ and $\sigma_{w_e,t}/\sigma_{Y,t}$), and the relative volatility of aggregate fintech credit ($\sigma_{X_f,t}/\sigma_{Y,t}$). At the same time, having a greater average measure of fintech intermediaries puts upward pressure on the relative volatility of labor

[12] Of note, were we to hold the total number of e firms at its baseline value, $\left(N_i + N_e^f\right)/N$ would increase by 0.34 percentage points to 20.34 percent, which is still a negligible change considering the sharp expansion in the number of fintech intermediaries.

[13] The benchmark economy generates a relative volatility of real *average* wages that is greater than 1, which is consistent with existing evidence on wage volatility in EMEs (see, for example, Li, 2011), but does not produce a relative volatility of consumption that is greater than 1. This, however, does not affect our main conclusions. Indeed, a richer version of our framework with both endogenous fintech-intermediary and traditional-bank entry under oligopolistic competition delivers a relative volatility of consumption greater than 1 without changing the conclusions from our baseline analysis (see Tables A4 and A6 in Appendix A.2).

and wages among i firms ($\sigma_{L_i,t}/\sigma_{Y,t}$ and $\sigma_{w_i,t}/\sigma_{Y,t}$), and makes consumption and bank credit more volatile relative to output ($\sigma_{c,t}/\sigma_{Y,t}$ and $\sigma_{X_b,t}/\sigma_{Y,t}$; while not shown, the cyclicality of the trade balance-output ratio remains virtually unchanged). We note, though, that the increase in relative volatilities is driven solely by the non-trivial reduction in output volatility as opposed to an increase in absolute volatilities.

All told, greater fintech intermediary entry generates asymmetric changes in volatility across firm categories, ultimately leading to an increase in relative volatility in key macroeconomic variables, including bank credit. The results in Table 4 are particularly noteworthy because, even after their sharp expansion, fintech intermediaries still account for a small share of total credit and only cater to a very small fraction of firms in the economy (see Table 3). More broadly, these findings imply that the expansion in the measure of fintech intermediaries can have an outsized influence on aggregate credit and macroeconomic dynamics.

Similar to the results in Table 3, the underlying source of the steady-state increase in fintech intermediaries shapes the quantitative change in relative volatilities and, in the case of aggregate credit, the direction of the change in its relative volatility. Specifically, a steady-state increase in fintech intermediaries rooted in a lower ψ_f leads to a much larger decrease in output volatility compared to a case where the increase in fintech intermediaries is rooted in a lower ψ_a. This, in turn, explains the larger changes in relative volatilities amid a lower ψ_f. To understand why the relative volatility of aggregate credit increases amid a lower ψ_f but falls amid a lower ψ_a, note that when greater fintech intermediary entry is driven by a sharp increase in the measure of e firms that use fintech credit as opposed to lower sunk entry costs for intermediaries, the contribution of fintech credit to aggregate credit is larger (see Table 3). Coupled with the much larger reduction in relative volatility in fintech credit and the more subdued increase in the relative volatility of bank credit, this contributes to a reduction in the relative volatility of aggregate credit ($\sigma_{Xt}/\sigma_{Y,t}$).

Table 4: Changes in Business Cycle Volatility: Benchmark Economy and Economy with Greater Fintech Intermediary Entry (via Reduction in ψ_f or Reduction in ψ_a)

Standard Deviations	**Benchmark Economy**	**Greater Fintech Intermediary Entry**			
		Via Lower ψ_f	**Percent Change (2) Relative to (1)**	**Via Lower ψ_a**	**Percent Change (4) Relative to (1)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
$\sigma_{Y,t}$	3.03	2.89	**-4.51%**	2.98	**-1.70%**
$\sigma_{c,t}/\sigma_{Y,t}$	0.88	0.90	**1.40%**	0.89	**0.80%**
$\sigma_{inv,t}/\sigma_{Y,t}$	3.17*	3.24	**2.04%**	3.10	**-2.21%**
$\sigma_{w_i,t}/\sigma_{Y,t}$	1.32	1.37	**3.79%**	1.34	**1.34%**
$\sigma_{w_e,t}/\sigma_{Y,t}$	0.85	0.76	**-11.12%**	0.84	**-0.81%**
$\sigma_{L_i,t}/\sigma_{Y,t}$	0.80	0.83	**4.04%**	0.81	**1.54%**
$\sigma_{L_e,t}/\sigma_{Y,t}$	0.49	0.43	**-12.96%**	0.49	**-0.99%**
$\sigma_{X_b,t}/\sigma_{Y,t}$	2.42*	2.51	**3.91%**	2.45	**1.31%**
$\sigma_{X_f,t}/\sigma_{Y,t}$	2.98	2.31	**-22.54%**	2.15	**-27.77%**
$\sigma_{X,t}/\sigma_{Y,t}$	2.47	2.49	**0.53%**	2.40	**-2.85%**

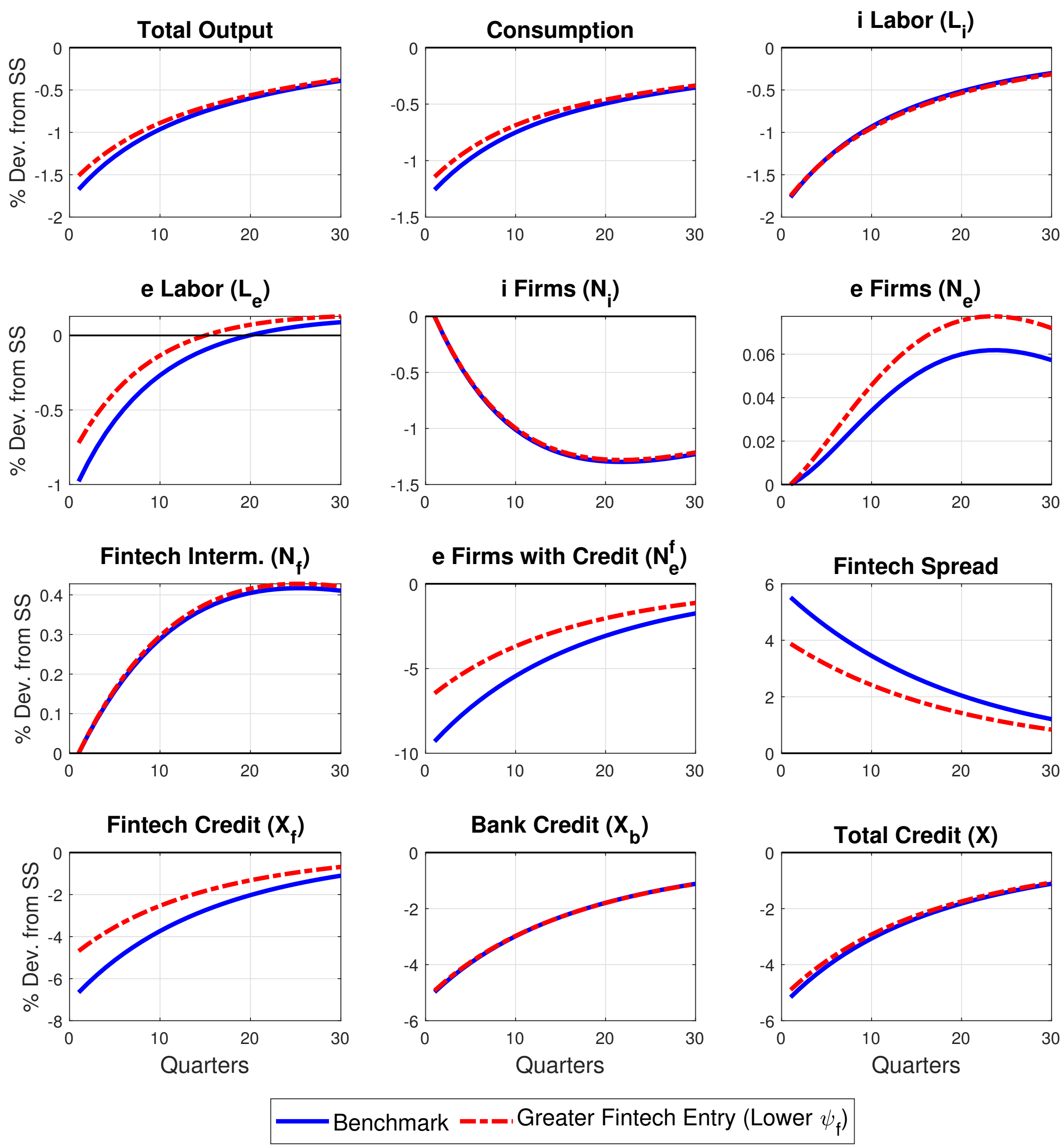
Notes: All real variables are expressed in data-consistent terms unless otherwise noted. To compute cyclical dynamics, we log-linearize the model and use a first-order approximation of the equilibrium conditions. We simulate the model for 2000 periods and compute second moments using an HP filter with smoothing parameter 1600. An * denotes a targeted second moment. Percent changes in **blue** represent beneficial changes (volatility-wise) relative to the benchmark economy. Percent changes in **red** represent adverse changes (volatility-wise) relative to the benchmark economy.

Driving Forces and Mechanisms To understand the key driving forces behind the results in Table 4, we consider the model's impulse responses to each shock in the benchmark economy and in the economy with greater steady-state fintech intermediary entry. For illustrative purposes and without loss of generality, we consider the case where greater fintech intermediary entry stems from a lower ψ_f. A cursory view of the impulse responses makes clear that the differential response to domestic financial shocks is the primary driver of the changes in relative volatility in Table 4. As such, for expositional brevity, we center on the response to domestic financial shocks and only briefly discuss the impulse responses to aggregate productivity and to foreign interest rate shocks.

A temporary adverse aggregate productivity shock is, as expected, recessionary in both the benchmark model and under greater steady-state fintech intermediary entry: total output, consumption, labor, credit, and the measure of firms across categories all contract in the aftermath of the shock (see Figure A1 in Appendix A.2.1). Importantly, conditional on these shocks, greater fintech intermediary entry has, for all intents and purposes, no discernible differential short-term macroeconomic and financial effects. A similar conclusion holds in response to an adverse foreign interest rate shock (see Figure A2 in Appendix A.2.2). These findings are worth pointing out for two reasons. First, it is well known in the literature that these two shocks play a prominent role in driving EME business cycles, and our model can produce factual dynamics in response to these two shocks in the presence of our two new margins (fintech intermediary entry and e-firm fintech credit adoption). Second, the fact that greater fintech intermediary entry does not meaningfully change the economy's response to these two shocks provides useful information regarding the channels and mechanisms via which greater fintech entry can affect the broader economy.

With this in mind, Figure 1 plots the responses of the benchmark economy (solid blue line) and the economy amid greater steady-state fintech intermediary entry (due to a lower ψ_f) (dash-dotted red line) to an identical one-standard-deviation temporary adverse aggregate domestic financial shock (i.e., a joint reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$). Recall that this last shock, which induces a temporary and simultaneous increase in bank and fintech intermediary lending rates and spreads, allows the benchmark economy to replicate the relative volatility of bank credit in our EME sample.

Figure 1: Response to a Temporary Adverse Domestic Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$)



In response to the shock, the economy with greater steady-state fintech intermediary entry exhibits a more subdued contraction in total output. As we discuss below, this smaller overall contraction is driven by the less sensitive response of e-firm variables to the shock. To better understand the results in Figure 1, recall that, per Table 3, greater average fintech intermediary entry reduces average lending rates and spreads for the subset of e firms that decide to use fintech credit. As such, for a given adverse domestic financial shock, the shock-induced increase in fintech intermediary lending rates (which all else equal bolsters lending spreads and financial intermediaries' profits and explains the expansion of fintech intermediaries) is smaller amid greater steady-state fintech intermediary entry. Recalling that one of the components of the marginal cost of e firms that use fintech credit is the fintech lending rate, the smaller increase in the cost of lending limits the shock-induced rise in the marginal cost of those firms. In turn, this contributes to the smaller contraction in the measure of e firms that use fintech credit, their output, and their labor (not shown). Then, given these dynamics, the response of these firms contributes to a smaller equilibrium contraction in fintech credit itself. The smaller contraction in the measure of e firms with fintech credit, coupled with the fact that e firms without credit are not directly impacted by the domestic financial shock, further limits the contraction in total e labor, thereby stabilizing household income (not shown). Turning to i firms, since the domestic financial shock affects both banks and fintech intermediaries and the measure of banks is fixed, the shock-induced increase in bank lending rates and spreads (not shown) is identical in the two scenarios. As such, the response of i firms, i labor, and bank credit compared to the benchmark model remains little changed.[14]

All told, the most notable finding is that, despite accounting for less than 5 percent of the total measure of firms, the more subdued contraction in the number of e firms with fintech credit, their labor, and their output under greater average fintech intermediary entry is powerful enough to limit the contraction in total output in response to adverse aggregate domestic financial shocks. This, in turn, implies that *relative to the response of output*, i-firm variables remain more responsive to domestic financial shocks under greater fintech intermediary entry, which explains the increase in the relative volatility of bank and aggregate credit, investment, and i-firm labor and wages in Table 4.

[14] We note that this result continues to hold when we allow for endogenous movements in the measure of banks.

4.2.3 Additional Results and Robustness Analysis

Macro and Credit Market Volatility from Fintech vs. Bank Expansion A natural question is whether an increase in the total amount of credit stemming from an increase in the measure of traditional banks has similar consequences for credit market and macroeconomic dynamics. To answer this question in a comparable way, we consider an exogenous increase in the baseline measure of banks B that generates the same steady-state percent increase in total credit as in the case where total credit increases due to greater fintech intermediary entry. Table A1 in Appendix A.2.4 compares the changes in volatility in this experiment to those stemming from an increase in the average measure of fintech intermediaries (via a reduction in ψ_f), which were originally shown in column (3) of Table 4.[15] Qualitatively, both a greater measure of fintech intermediaries and banks generate lower output volatility. However, Table A1 makes clear that there are non trivial compositional effects: an increase in the measure of banks generates more fintech-credit volatility and labor volatility among e firms but reduces bank-credit and aggregate-credit volatility, as well as labor volatility among i firms. More importantly, for the same average increase in total credit, greater fintech intermediary entry generates a larger increase in relative volatility across a host of variables. This points to the importance of the composition of total credit and its implications for credit market volatility in a context with fintech intermediation.

Greater Baseline Share of Firms with Credit and Identical Firm Sunk Entry Costs Table A2 and Figures A4 and A5 in Appendix A.2 show that assuming a baseline share of firms with credit (either from banks or fintech intermediaries) that is twice as large as the share in the benchmark calibration merely reduces the differential in sunk entry costs between firm categories but leaves our quantitative results unchanged. Assuming that e and i firms face identical sunk entry costs only changes the baseline share of firms with credit and does not change our main findings either.

[15]To confirm that the results in Table A1 are robust, we also conduct the same experiment in versions of the benchmark model that allow for the endogenous creation of banks, where the increase in the measure of banks is rooted in an exogenous reduction in the sunk cost of bank entry (see Table A4 in Appendix A.2.6 and A6 in Appendix A.2.7 for more details).

Fintech Intermediary Entry Costs and Foreign Interest Rate Shocks Assuming that the sunk cost of fintech intermediary entry is directly affected by foreign interest rate shocks—a plausible scenario where fintech intermediaries depend on foreign funding as a direct source of startup funds—generates the same changes in relative volatility amid greater fintech intermediary entry as those in our benchmark model (results available upon request). These results suggest that it is indeed disturbances in domestic credit markets that drive the impact of greater fintech intermediary entry on cyclical macro-financial dynamics.

Endogenous Changes in Bank and Fintech Funding Costs In our framework, the steady-state gross deposit rates of banks and fintech intermediaries—that is, their funding costs—depend solely on the household's subjective discount factor. This implies that, while greater fintech intermediary entry affects the total amount of funds that banks use to finance loans for i firms, banks' funding costs and therefore their lending rates remain unaffected. Introducing convex deposit-adjustment costs makes banks' and fintech intermediaries' gross deposit interest rates a function of deposits and allows changes in these deposits—say, due to an increase in fintech intermediary entry—to affect banks' funding costs (these costs can represent, in a reduced-form way, monitoring costs in the presence of asymmetric information in credit markets). This richer environment delivers results that are quantitatively identical to those in our benchmark framework: while greater fintech intermediary entry does put upward pressure on banks' funding costs by reallocating deposits away from banks and into fintech intermediaries, the changes in these costs are quantitatively negligible (results available upon request).

Endogenous Traditional Bank Entry Table A3 and Figures A6 and A7 in Appendix A.2 show that our main findings continue to hold when we allow for endogenous traditional bank creation alongside fintech intermediary entry. In fact, our quantitative results become somewhat stronger when bank entry is endogenous.

Oligopolistic Competition in Credit Markets Our baseline model assumes monopolistic competition in financial intermediation under Dixit-Stiglitz preferences, which implies that lending-deposit spreads among traditional banks and fintech intermediaries are constant. Introducing oligopolistic competition between traditional banks and between fintech intermediaries endogenizes lending-deposit rate markups in each financial intermediation category: these markups become a function of the measure of financial intermediaries in their respective category. As shown in Table A5 and Figures A8 and A9 of Appendix A.2, allowing for oligopolistic competition in credit markets amid endogenous entry of banks and fintech intermediaries does not change our main conclusions.[16]

5 Conclusion

Emerging economies (EMEs) have considerably lower levels of domestic firm financial participation compared to advanced economies, reflected in large shares of firms that are excluded from the banking system. Importantly, these firms account for a significant share of both employment and economic activity. The steady adoption of digital technologies in EMEs in recent years has been accompanied by the emergence and fast expansion in the number of non-traditional financial intermediaries whose business model leverages the use of digital technologies to provide financial services to firms and individuals who face high barriers to participation in the traditional banking system. This, coupled with the fact that fintech intermediaries may compete for resources with the traditional banking system, raises important questions about the consequences of the sharp expansion in the number of fintech intermediaries in EMEs for aggregate firm financial inclusion and macro-financial outcomes.

We propose a framework with endogenous firm entry, a traditional banking system, and endogenous fintech intermediary creation. In our model, firms differ in their sources of credit and the economy's degree of firm financial inclusion is endogenous. Calibrating the model to match key characteristics of EME business cycles and bank credit dynamics, we quantitatively characterize the financial inclusion and macro-financial implications of greater fintech intermediary entry. Our quantitative results suggest that greater fintech intermediary entry can have positive long-term macroeconomic effects by leading to greater overall firm creation

[16]For models with bank entry and oligopolistic competition in the banking system, see Stebunovs (2008) and Toltzek (2011). For a model with firm entry, oligopolistic competition in the goods market, and frictionless credit markets, see Colciago and Etro (2010). Our approach to modeling endogenous traditional bank entry follows Totzek (2011), who adapts the goods-sector endogenous entry setup in Colciago and Etro (2011) to the banking sector.

and improved firm-level outcomes among firms that start off being financially excluded but, as a result of greater fintech entry, are able to access fintech credit. However, the resulting reallocation of resources towards these firms leads to a reduction in aggregate bank credit. Moreover, while greater fintech intermediary entry bolsters the number of firms with credit, it also brings about an increase in the total number of firms that fundamentally shapes the share of firms with credit—a summary measure of firm financial inclusion. Depending on the root cause of the increase in fintech intermediary entry—a lower entry cost for these intermediaries (a supply-driven expansion) or lower barriers to accessing fintech credit by firms (a demand-driven expansion)—for the same increase in fintech intermediary entry, the share of firms with credit can increase or remain virtually unchanged. We find that at the aggregate level, the expansion of fintech intermediaries may not meaningfully contribute to greater firm financial inclusion if firms' barriers to accessing fintech credit remain unchanged.

In an environment that replicates the cyclical volatility of bank credit in EMEs, greater fintech intermediary entry leads to a non- trivial reduction in output volatility, where this reduction is driven by the more subdued behavior of firms that use fintech credit in response to domestic financial shocks. In contrast, greater fintech intermediary entry has negligible effects on the behavior of firms that rely on bank credit amid these shocks. As a result, greater fintech intermediary entry generates an increase in the relative volatility of bank credit and ultimately consumption. Our findings may have broader policy implications: our results suggest that while greater fintech intermediary entry in EMEs has positive effects on long-run macro aggregates and volatility-reducing effects on total output, its quantitative impact on aggregate firm financial inclusion and credit market volatility hinges critically on the underlying factors driving the growth in fintech intermediary entry.

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A Online Appendix

A.1 Equilibrium Conditions: Benchmark Model

Taking the stochastic processes $\left\{z_{i,t}, z^n_{e,t}, z^f_{e,t}, \varepsilon_{b,t}, \varepsilon_{f,t}\right\}$ as given, the allocations and prices $\{Y_t, Y_{i,t}, Y_{e,t}\}$, $\left\{y_{i,t}, l^n_{e,t}, l^f_{e,t}, n_{i,t}, c_t, R^b_{d,t}, R^f_{d,t}, d_{f,t}, L_{i,t}, L_{e,t}, H_{e,t}, H_{i,t}, \pi_{e,t}, H_{f,t}, N_{i,t}, N_{e,t}, N_{f,t}\right\}$, and $\left\{R^b_{l,t}, R^f_{l,t}, \rho_{i,t}, \widetilde{\rho}^n_{e,t}, \widetilde{\rho}^n_{e,t}, N^f_{e,t}, \overline{a}_{e,t}, \widetilde{a}^n_{e,t}, \widetilde{a}^f_{e,t}, \widetilde{\pi}^n_{e,t}, \widetilde{\pi}^f_{e,t}, \widetilde{y}^n_{e,t}, \widetilde{y}^f_{e,t}, w_{i,t}, w_{e,t}, r^b_{l,t}, r^f_{l,t}, p_{e,t}, p_{i,t}, \rho_{e,t}, D_{f,t}, D^*_t\right\}$ satisfy:

$$Y_t = \left[\alpha_y^{\frac{1}{\phi_y}} \left(Y_{i,t}\right)^{\frac{\phi_y - 1}{\phi_y}} + (1-\alpha_y)^{\frac{1}{\phi_y}} \left(Y_{e,t}\right)^{\frac{\phi_y - 1}{\phi_y}}\right]^{\frac{\phi_y}{\phi_y - 1}}, \tag{19}$$

$$Y_t = c_t + \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_f H_{f,t} + \psi_a N^f_{e,t} + S_{t-1} R^*_{t-1} D^*_{t-1} + D^*_t + \frac{\eta^*}{2}(D^*_t)^2, \tag{20}$$

$$Y_{i,t} = N_{i,t}^{\frac{\varepsilon}{\varepsilon-1}} y_{i,t}, \tag{21}$$

$$Y_{e,t} = \left(N^n_{e,t}\left(\widetilde{y}^n_{e,t}\right)^{\frac{\varepsilon-1}{\varepsilon}} + N^f_{e,t}\left(\widetilde{y}^f_{e,t}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{22}$$

$$y_{i,t} = z_{i,t} l_{i,t}, \tag{23}$$

$$L_{e,t} = N^n_{e,t} l^n_{e,t} + N^f_{e,t} l^f_{e,t}, \tag{24}$$

$$L_{i,t} = l_{i,t} N_{i,t}, \tag{25}$$

$$1 = \mathbb{E}_t \Xi_{t+1|t} R^b_{d,t}, \tag{26}$$

$$1 = \mathbb{E}_t \Xi_{t+1|t} R^f_{d,t}, \tag{27}$$

$$1 = \mathbb{E}_t \Xi_{t+1|t} S_t R^*_t + \eta^*(D^*_t), \tag{28}$$

$$D_{f,t} = \kappa_e \left(w_{e,t} n^f_{e,t} + \psi_a\right) N^f_{e,t}, \tag{29}$$

$$-u_{L_i,t} = w_{i,t} u_{c,t}, \tag{30}$$

$$-u_{L_e,t} = w_{e,t} u_{c,t}, \tag{31}$$

$$\psi_e = (1-\delta)\mathbb{E}_t \Xi_{t+1|t}\left[\pi_{e,t+1} + \psi_e\right], \tag{32}$$

$$\psi_i\left(1-\kappa_i+\kappa_i R^b_{l,t}\right) = (1-\delta)\mathbb{E}_t \Xi_{t+1|t}\left[\left(\rho_{i,t+1} - \frac{\left(1-\kappa_i+\kappa_i R^b_{l,t+1}\right) w_{i,t+1}}{z_{i,t+1}}\right) y_{i,t+1}\right], \quad (33)$$

$$+ (1-\delta)\mathbb{E}_t \Xi_{t+1|t}\left[\psi_i\left(1-\kappa_i+\kappa_i R^b_{l,t+1}\right)\right]$$

$$\pi_{e,t} = \left(\frac{N_{e,t} - N^f_{e,t}}{N_{e,t}}\right)\widetilde{\pi}^n_{e,t} + \left(\frac{N^f_{e,t}}{N_{e,t}}\right)\widetilde{\pi}^f_{e,t}, \quad (34)$$

$$\psi_f = (1-\delta_f)\mathbb{E}_t \Xi_{t+1|t}\left[\left(r^f_{l,t+1} - R^f_{d,t+1}\right) d_{f,t+1} + \psi_f\right], \quad (35)$$

$$N_{i,t+1} = (1-\delta)(N_{i,t} + H_{i,t}), \quad (36)$$

$$N_{e,t+1} = (1-\delta)(N_{e,t} + H_{e,t}), \quad (37)$$

$$N_{f,t+1} = (1-\delta_f)(N_{f,t} + H_{f,t}), \quad (38)$$

$$r^b_{l,t} = \mu_{b,t} R^b_{d,t}, \quad (39)$$

$$r^f_{l,t} = \mu_{f,t} R^f_{d,t}, \quad (40)$$

$$\rho_{i,t} = \left(\frac{\varepsilon}{\varepsilon-1}\right)\frac{\left(1-\kappa_i+\kappa_i R^b_{l,t}\right) w_{i,t}}{z_{i,t}}, \quad (41)$$

$$\widetilde{\rho}^n_{e,t} = \left(\frac{\varepsilon}{\varepsilon-1}\right)\frac{w_{e,t}}{z^n_{e,t}\widetilde{a}^n_{e,t}}, \quad (42)$$

$$\widetilde{\rho}^f_{e,t} = \left(\frac{\varepsilon}{\varepsilon-1}\right)\frac{\left(1-\kappa_e+\kappa_e R^f_{l,t}\right) w_{e,t}}{z^f_{e,t}\widetilde{a}^f_{e,t}}, \quad (43)$$

$$N^f_{e,t} = \left[1-G(\overline{a}_{e,t})\right] N_{e,t}, \quad (44)$$

$$\pi^n_{e,t}(\overline{a}_{e,t}) = \pi^f_{e,t}(\overline{a}_{e,t}), \quad (45)$$

$$\widetilde{a}^n_{e,t} = \widetilde{a}^f_{e,t}\left(\frac{\overline{a}^{k_p-(\varepsilon-1)}_{e,t} - a^{k_p-(\varepsilon-1)}_{min}}{\overline{a}^{k_p}_{e,t} - a^{k_p}_{min}}\right)^{\frac{1}{\varepsilon-1}} a_{min}, \quad (46)$$

$$\widetilde{a}^f_{e,t} = \left(\frac{k_p}{k_p-(\varepsilon-1)}\right)^{\frac{1}{\varepsilon-1}}\overline{a}_{e,t}, \quad (47)$$

$$\widetilde{\pi}^n_{e,t} = \left(\widetilde{\rho}^n_{e,t} - \frac{w_{e,t}}{z_{e,t}\widetilde{a}^n_{e,t}}\right)\widetilde{y}^n_{e,t}, \quad (48)$$

$$\widetilde{\pi}_{e,t}^{f} = \left(\widetilde{\rho}_{e,t}^{f} - \frac{w_{e,t}\left(1-\kappa_e+\kappa_e R_{l,t}^{f}\right)}{z_{e,t}\widetilde{a}_{e,t}^{f}}\right)\widetilde{y}_{e,t}^{f} - \psi_a\left(1-\kappa_e+\kappa_e R_{l,t}^{f}\right), \tag{49}$$

$$\widetilde{y}_{e,t}^{n} = z_{e,t}^{n}\widetilde{a}_{e,t}^{n} l_{e,t}^{n}, \tag{50}$$

$$\widetilde{y}_{e,t}^{f} = z_{e,t}^{f}\widetilde{a}_{e,t}^{f} l_{e,t}^{f}, \tag{51}$$

$$Y_{i,t} = \alpha_y \left(p_{i,t}\right)^{-\phi_y} Y_t, \tag{52}$$

$$Y_{e,t} = \left(1-\alpha_y\right)\left(p_{e,t}\right)^{-\phi_y} Y_t, \tag{53}$$

$$\widetilde{y}_{e,t}^{n} = \left(\frac{\widetilde{\rho}_{e,t}^{n}}{p_{e,t}}\right)^{-\varepsilon} Y_{e,t}, \tag{54}$$

$$\widetilde{y}_{e,t}^{f} = \left(\frac{\widetilde{\rho}_{e,t}^{f}}{p_{e,t}}\right)^{-\varepsilon} Y_{e,t}, \tag{55}$$

$$r_{l,t}^{f} = N_{f,t}^{\frac{1}{\varepsilon_f - 1}} R_{l,t}^{f}, \tag{56}$$

$$r_{l,t}^{b} = B^{\frac{1}{\varepsilon_b - 1}} R_{l,t}^{b}, \tag{57}$$

$$p_{i,t} = N_{i,t}^{\frac{1}{1-\varepsilon}} \rho_{i,t}, \tag{58}$$

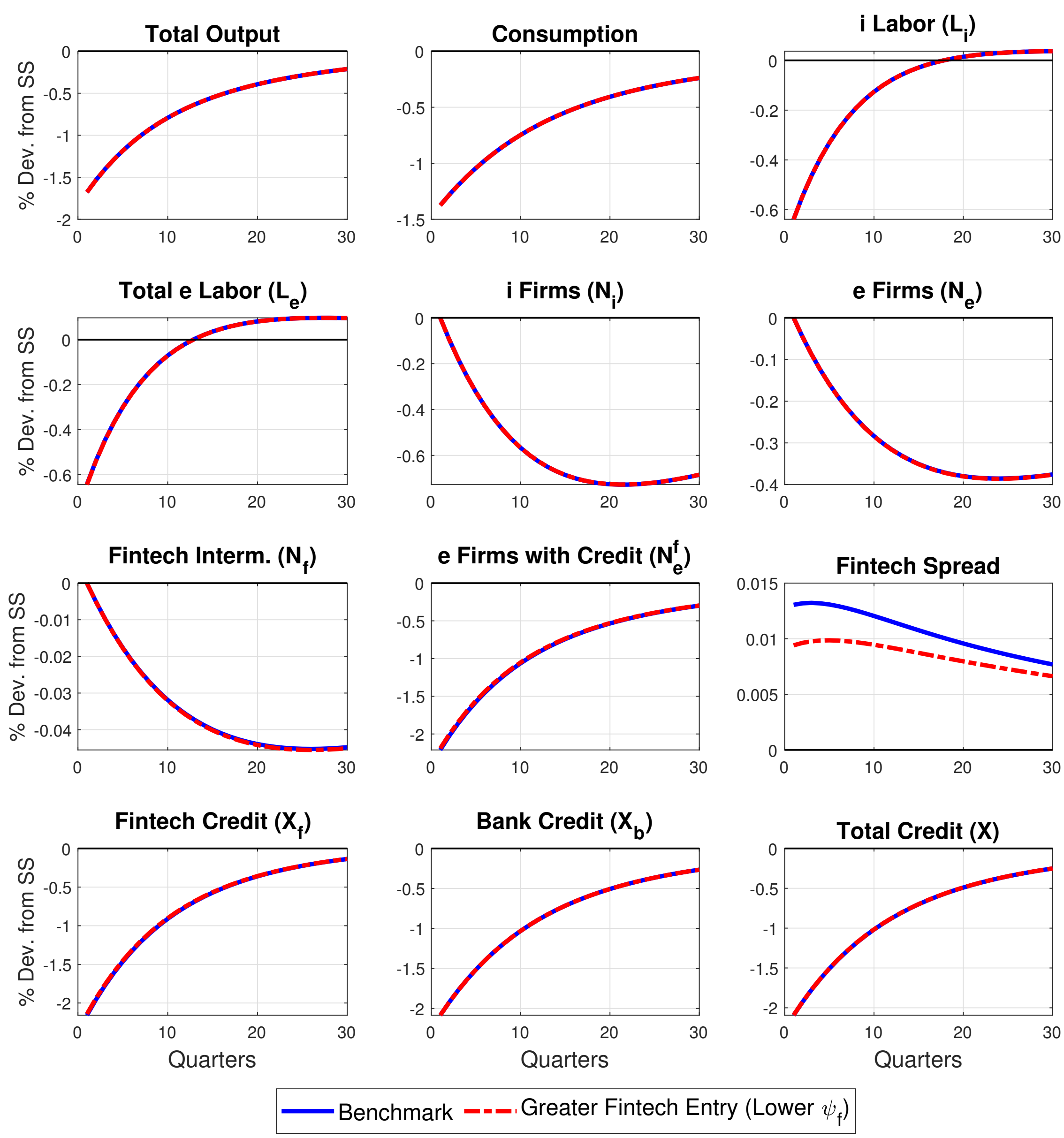
$$p_{e,t} = N_{e,t}^{\frac{1}{1-\varepsilon}} \rho_{e,t}, \tag{59}$$

$$D_{f,t} = N_{f,t}^{\frac{\varepsilon_f}{\varepsilon_f - 1}} d_{f,t}. \tag{60}$$

A.2 Additional Results and Robustness Checks

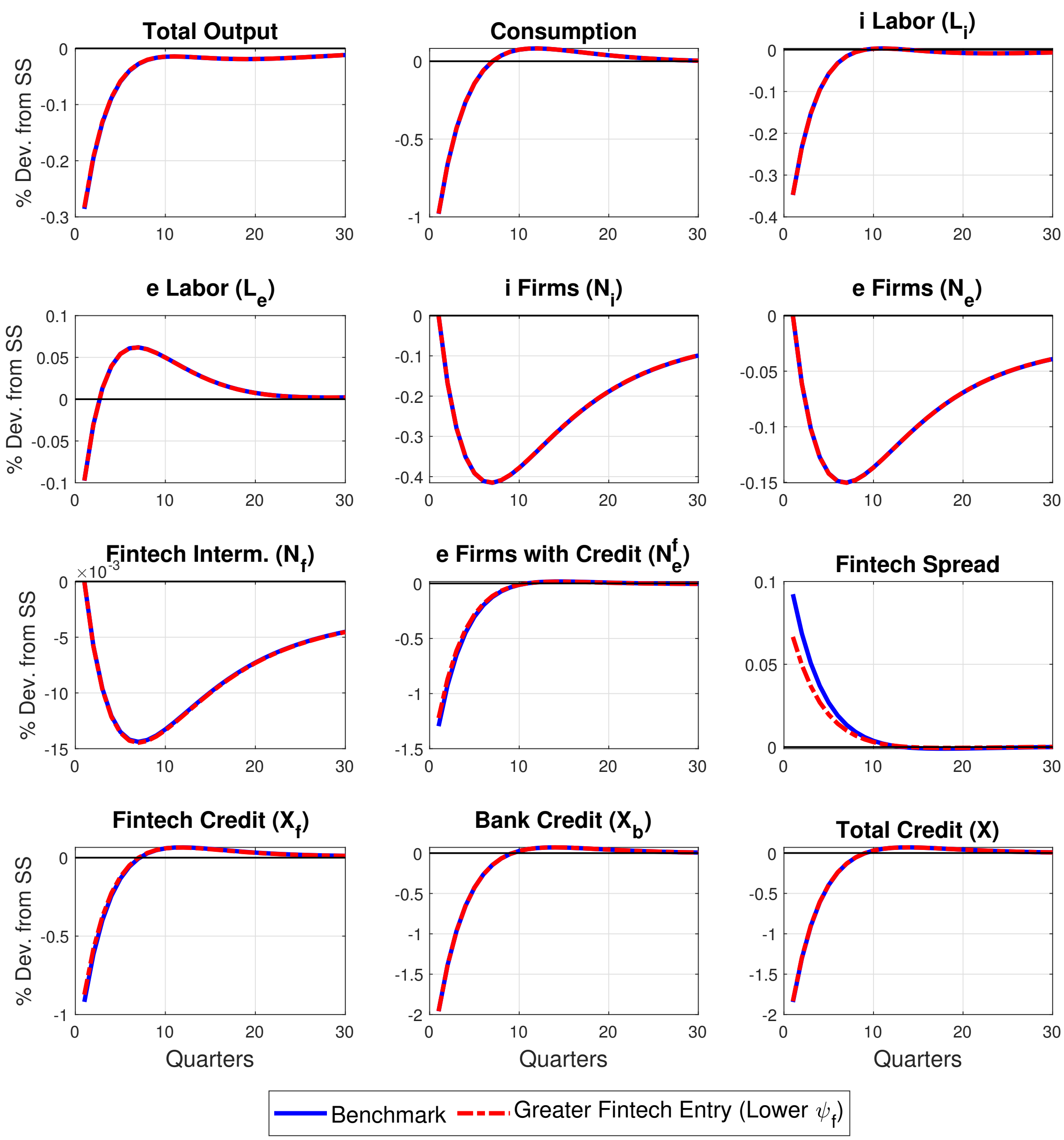
A.2.1 Benchmark Model Impulse Responses: Adverse Shock to Aggregate Productivity

Figure A1: Response to a Temporary Adverse Aggregate Productivity Shock



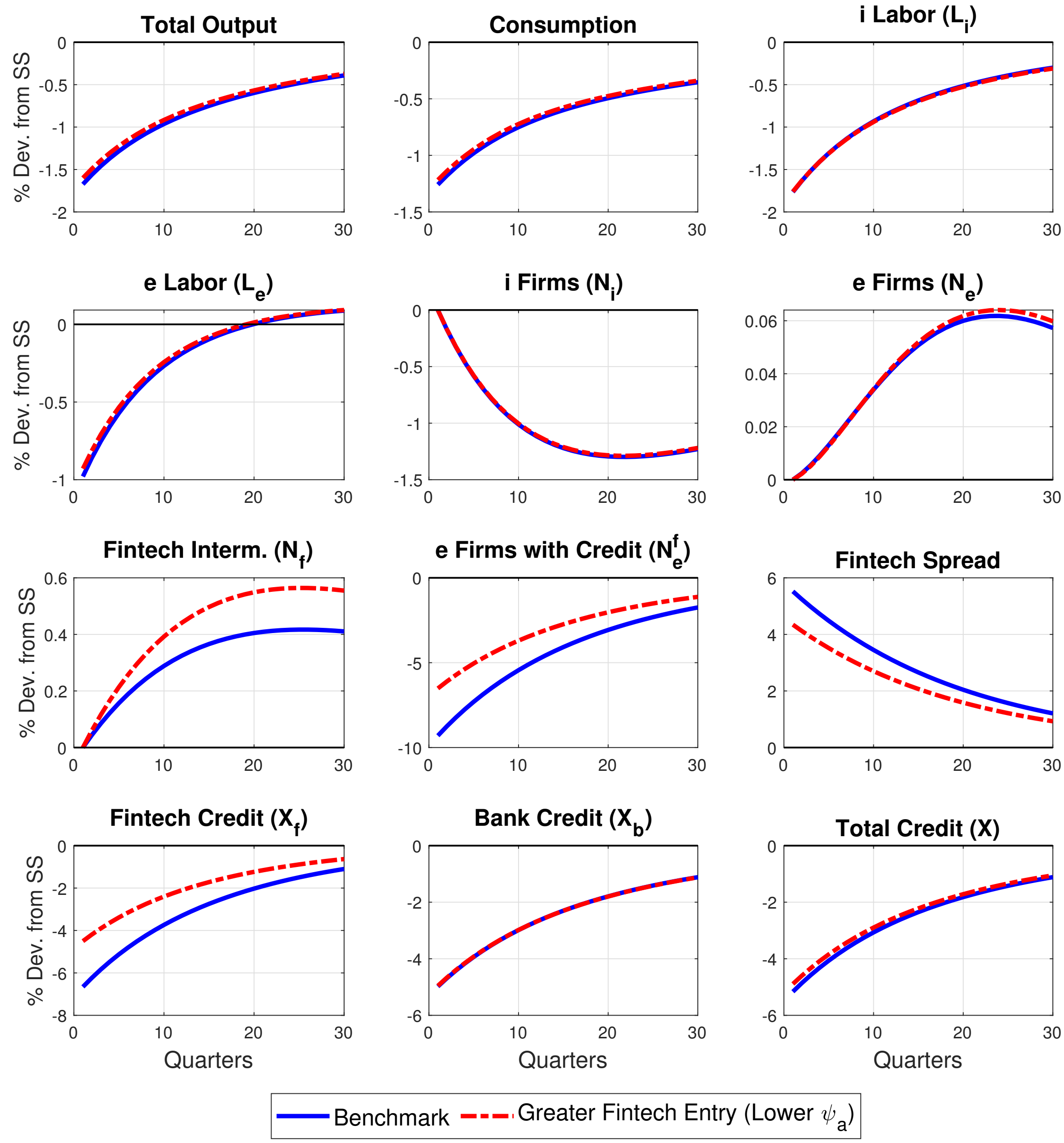
A.2.2 Benchmark Model Impulse Responses: Adverse Shock to Foreign Interest Rate

Figure A2: Response to a Temporary Adverse Foreign Interest Rate Shock



A.2.3 Benchmark Model Impulse Responses: Adverse Shock to Domestic Financial Shock with Lower ψ_a

Figure A3: Response to a Temporary Adverse Domestic Financial Shock



A.2.4 Macro and Credit Market Volatility: Fintech vs. Banks

Table A1: Changes in Business Cycle Volatility: Benchmark Economy, Economy with Greater Fintech Intermediary Entry (via Reductions in ψ_f or ψ_a), and Economy with Greater Measure of Traditional Banks (via Increase in B)

Second Deviations	**Economy with Greater Fintech Interm. Entry via Lower ψ_f**	**Economy with Greater Fintech Interm. Entry via Lower ψ_a**	**Economy with Greater Measure of Banks B**
	Percent Change Relative to Benchmark	**Percent Change Relative to Benchmark**	**Percent Change Relative to Benchmark**
$\sigma_{Y,t}$	**-4.51%**	**-1.70%**	**-0.43%**
$\sigma_{c,t}/\sigma_{Y,t}$	**1.40%**	**0.80%**	**0.10%**
$\sigma_{inv,t}/\sigma_{Y,t}$	**2.04%**	**-2.21%**	**0.08%**
$\sigma_{w_i,t}/\sigma_{Y,t}$	**3.79%**	**1.34%**	**-0.64%**
$\sigma_{w_e,t}/\sigma_{Y,t}$	**-11.12%**	**-0.81%**	**0.32%**
$\sigma_{L_i,t}/\sigma_{Y,t}$	**4.04%**	**1.54%**	**-0.68%**
$\sigma_{L_e,t}/\sigma_{Y,t}$	**-12.96%**	**-0.99%**	**0.40%**
$\sigma_{X_b,t}/\sigma_{Y,t}$	**3.91%**	**1.31%**	**-0.52%**
$\sigma_{X_f,t}/\sigma_{Y,t}$	**-22.54%**	**-27.77%**	**0.39%**
$\sigma_{X,t}/\sigma_{Y,t}$	**0.53%**	**-2.85%**	**-0.42%**

Notes: All real variables are expressed in data-consistent terms unless otherwise noted. To compute cyclical dynamics, we log-linearize the model and use a first-order approximation of the equilibrium conditions. We simulate the model for 2,000 periods and compute second moments using an HP filter with smoothing parameter 1600. Percent changes in **blue** represent beneficial changes (volatility-wise) relative to the benchmark economy. Percent changes in **red** represent adverse changes (volatility-wise) relative to the benchmark economy.

A.2.5 Greater Baseline Share of Firms with Credit

Table A2: Steady-State Changes in Response to Greater Fintech Intermediary Entry (Reduction in ψ_f or in ψ_a), Benchmark vs. Higher Baseline Share of Firms with Credit

	Benchmark Model Calibration (lower ψ_f)	Benchmark Model Calibration (lower ψ_a)	Higher Baseline Share of Firms with Credit (lower ψ_f)	Higher Baseline Share of Firms with Credit (lower ψ_a)
Variable	**Change Relative to Baseline (% or PP)**	**Change Relative to Baseline (% or PP)**	**Change Relative to Baseline (% or PP)**	**Change Relative to Baseline (% or PP)**
Measure of Fintech Intermediaries N_f	52%	52%	52%	52%
Aggregate Output Y	0.48%	3.33%	0.48%	3.34%
Aggregate Consumption c	0.42%	2.89%	0.42%	2.90%
e-Firm Wage w_e	0.80%	4.39%	0.80%	4.40%
i-Firm Wage w_i	-0.37%	-3.68%	-0.37%	-3.68%
e Firms N_e	2.31%	22.91%	2.31%	22.91%
e Firms with Fintech Credit N_e^f	8.65%	358.43%	8.65%	359.58%
i Firms N_i	0.20%	0.41%	0.20%	0.41%
Aggregate Fintech Credit X_f	5.93%	47.98%	5.93%	48.08%
Aggregate Bank Credit X_b	-0.48%	-5.56%	-0.48%	-5.57%
Aggregate Credit X	0.23%	0.30%	0.23%	0.31%
Share of e Firms with Fintech Credit N_e^f/N_e	0.31 PP	13.65 PP	0.31 PP	13.69 PP
Total Share of Firms with Credit $\left(N_i + N_e^f\right)/N$	0.001 PP	9.45 PP	-0.26 PP	4.92 PP
Ave. Fintech Lending Spread $\left(R_l^f - R_d^f\right)$	-3.96 PP	-3.96 PP	-3.96 PP	-3.96 PP

Notes: $N \equiv (N_e + N_i)$ is the total measure of firms in the economy. All real variables are expressed in data-consistent terms unless otherwise noted. **PP denotes Percentage Points**.

Figure A4: Response to a Temporary Adverse Aggregate Productivity Shock, Higher Baseline Share of Firms with Credit

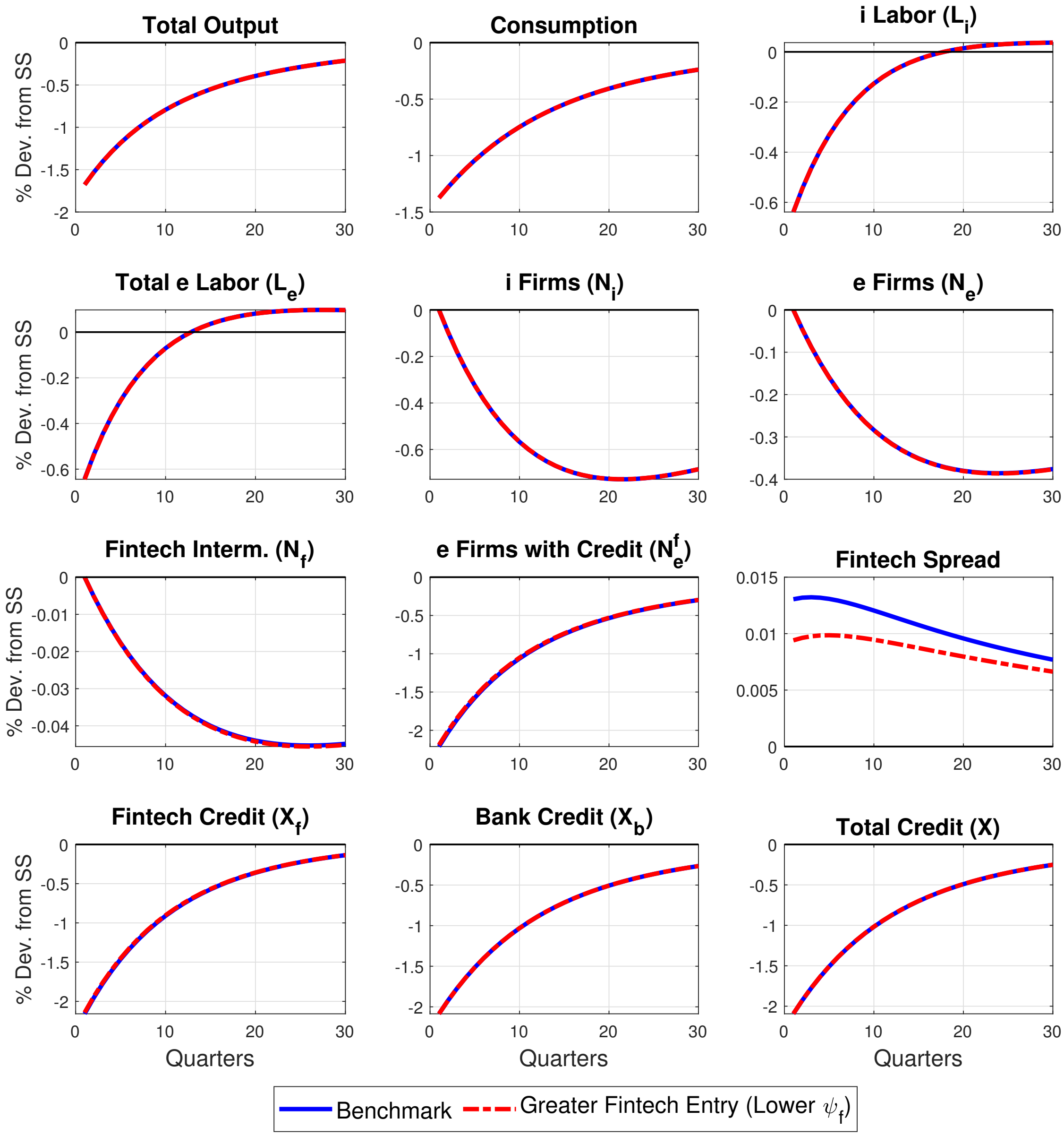
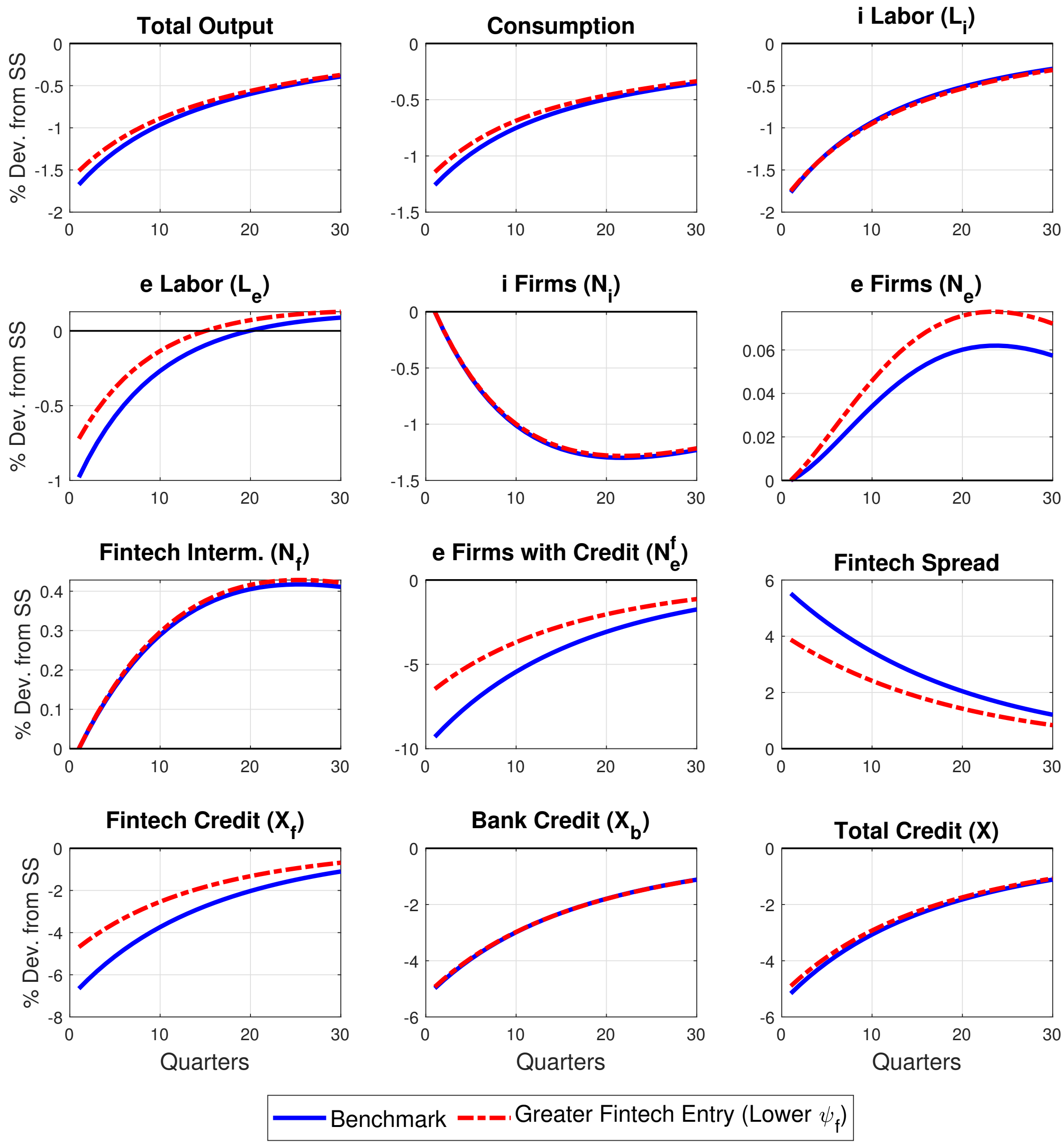


Figure A5: Response to a Temporary Adverse Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Higher Baseline Share of Firms with Credit



A.2.6 Model with Endogenous Traditional Bank Entry

Table A3: Steady-State Changes in Response to Greater Fintech Intermediary Entry (Reduction in ψ_f or in ψ_a), Model with Endogenous Bank Entry

	Benchmark Model Calibration (lower ψ_f)	Benchmark Model Calibration (lower ψ_a)	Model with Endogenous Traditional Bank Entry (lower ψ_f)	Model with Endogenous Traditional Bank Entry (lower ψ_a)
Variable	**Change Relative to Baseline (% or PP)**	**Change Relative to Baseline (% or PP)**	**Change Relative to Baseline (% or PP)**	**Change Relative to Baseline (% or PP)**
Measure of Fintech Intermediaries N_f	52%	52%	52%	52%
Aggregate Output Y	0.48%	3.33%	0.58%	3.42%
Aggregate Consumption c	0.42%	2.89%	0.53%	2.12%
e-Firm Wage w_e	0.80%	4.39%	0.97%	4.54%
i-Firm Wage w_i	-0.37%	-3.68%	-0.41%	-3.69%
e Firms N_e	2.31%	22.91%	2.72%	23.25%
e Firms with Fintech Credit N_e^f	8.65%	358.43%	10.37%	359.02%
i Firms N_i	0.20%	0.41%	0.28%	0.55%
Traditional Banks B	–	–	0.26%	0.50%
Aggregate Fintech Credit X_f	5.93%	47.98%	7.09%	48.93%
Aggregate Bank Credit X_b	-0.48%	-5.56%	-0.52%	-5.55%
Aggregate Credit X	0.23%	0.30%	0.50%	1.72%
Share of e Firms with Fintech Credit N_e^f/N_e	0.31 PP	13.65 PP	0.37 PP	13.62 PP
Total Share of Firms with Credit $\left(N_i + N_e^f\right)/N$	0.001 PP	9.45 PP	0.013 PP	9.42 PP
Ave. Fintech Lending Spread $\left(R_l^f - R_d^f\right)$	-3.96 PP	-3.96 PP	-4.74 PP	-4.74 PP

Notes: $N \equiv (N_e + N_i)$ is the total measure of firms in the economy. All real variables are expressed in data-consistent terms unless otherwise noted. **PP denotes Percentage Points**.

Table A4: Changes in Business Cycle Volatility: Model with Endogenous Bank and Fintech Indermediary Entry under Monopolistic Competition

Standard Deviations	**Benchmark Economy**	**Greater Fintech Fintech Entry (Lower ψ_f)**		**Greater Fintech Fintech Entry (Lower ψ_a)**		**Greater Bank Entry (Lower ψ_b)**	
		SD	**Percent Change Relative to Benchmark**	**SD**	**Percent Change Relative to Benchmark**	**SD**	**Percent Change Relative to Benchmark**
$\sigma_{Y,t}$	3.48	3.20	**-7.91%**	3.37	**-3.28%**	2.78	**-19.93%**
$\sigma_{c,t}/\sigma_{Y,t}$	0.98	1.02	**3.66%**	1.00	**1.45%**	1.06	**8.34%**
$\sigma_{inv,t}/\sigma_{Y,t}$	3.16*	3.31	**4.81%**	3.13	**-1.10%**	3.46	**9.45%**
$\sigma_{w_i,t}/\sigma_{Y,t}$	1.36	1.46	**7.70%**	1.41	**3.52%**	0.95	**-30.18%**
$\sigma_{w_e,t}/\sigma_{Y,t}$	0.99	0.83	**-15.91%**	0.96	**-3.75%**	1.18	**19.51%**
$\sigma_{L_i,t}/\sigma_{Y,t}$	0.82	0.88	**7.35%**	0.85	**3.81%**	0.55	**-33.17%**
$\sigma_{L_e,t}/\sigma_{Y,t}$	0.58	0.47	**-18.24%**	0.56	**-4.47%**	0.72	**24.67%**
$\sigma_{X_b,t}/\sigma_{Y,t}$	2.41*	2.59	**7.60%**	2.50	**3.42%**	1.85	**-23.34%**
$\sigma_{X_f,t}/\sigma_{Y,t}$	3.78	2.73	**-27.55%**	2.57	**-32.00%**	4.67	**23.41%**
$\sigma_{X,t}/\sigma_{Y,t}$	2.58	2.61	**1.08%**	2.50	**-3.15%**	2.13	**-17.60%**

Notes: All real variables are expressed in data-consistent terms unless otherwise noted. To compute cyclical dynamics, we log-linearize the model and use a first-order approximation of the equilibrium conditions. We simulate the model for 2,000 periods and compute second moments using an HP filter with smoothing parameter 1600. Percent changes in **blue** represent beneficial changes (volatility-wise) relative to the benchmark economy. Percent changes in **red** represent adverse changes (volatility-wise) relative to the benchmark economy.

Figure A6: Response to a Temporary Adverse Aggregate Productivity Shock, Model with Endogenous Bank and Fintech Intermediary Entry

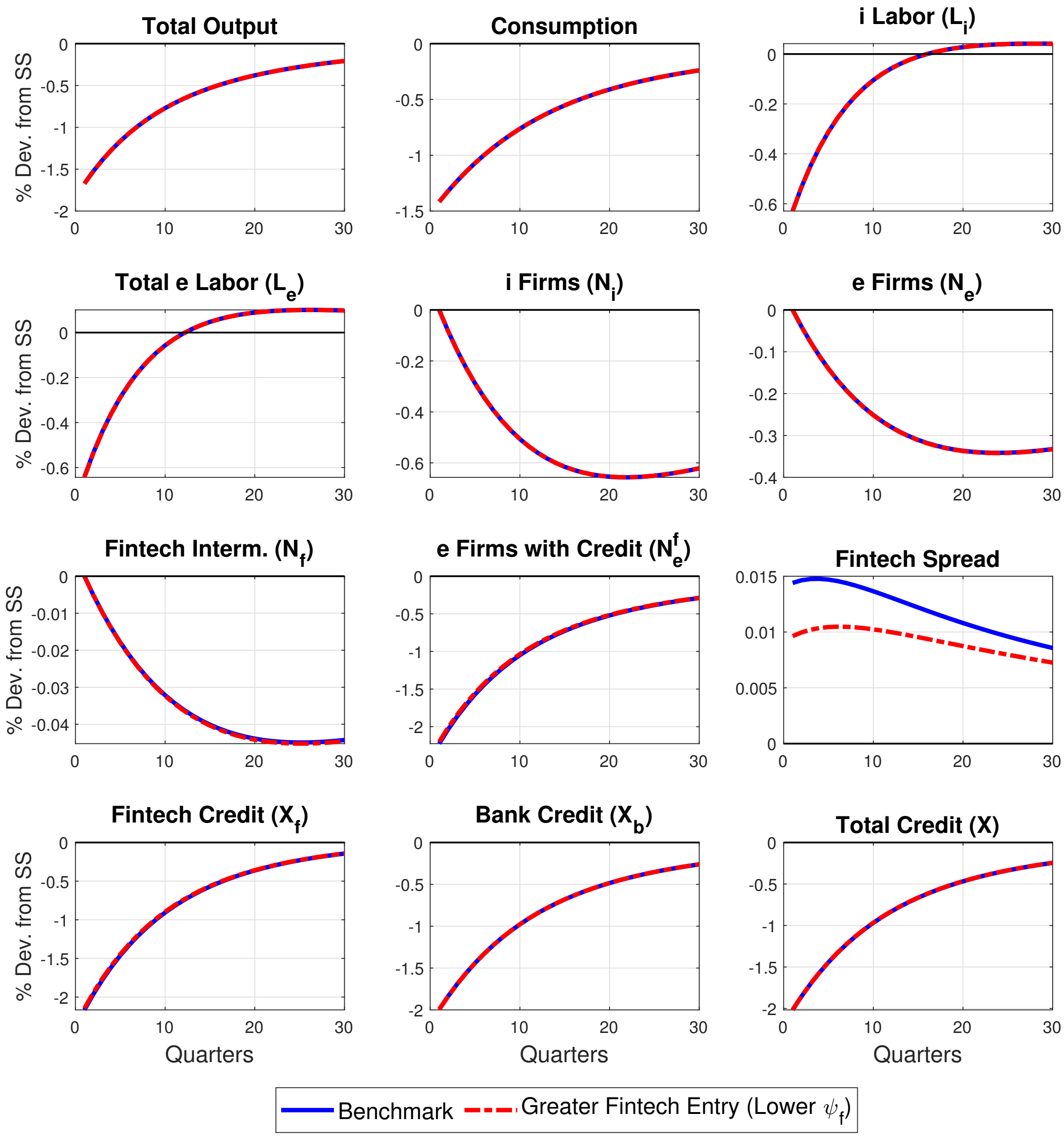
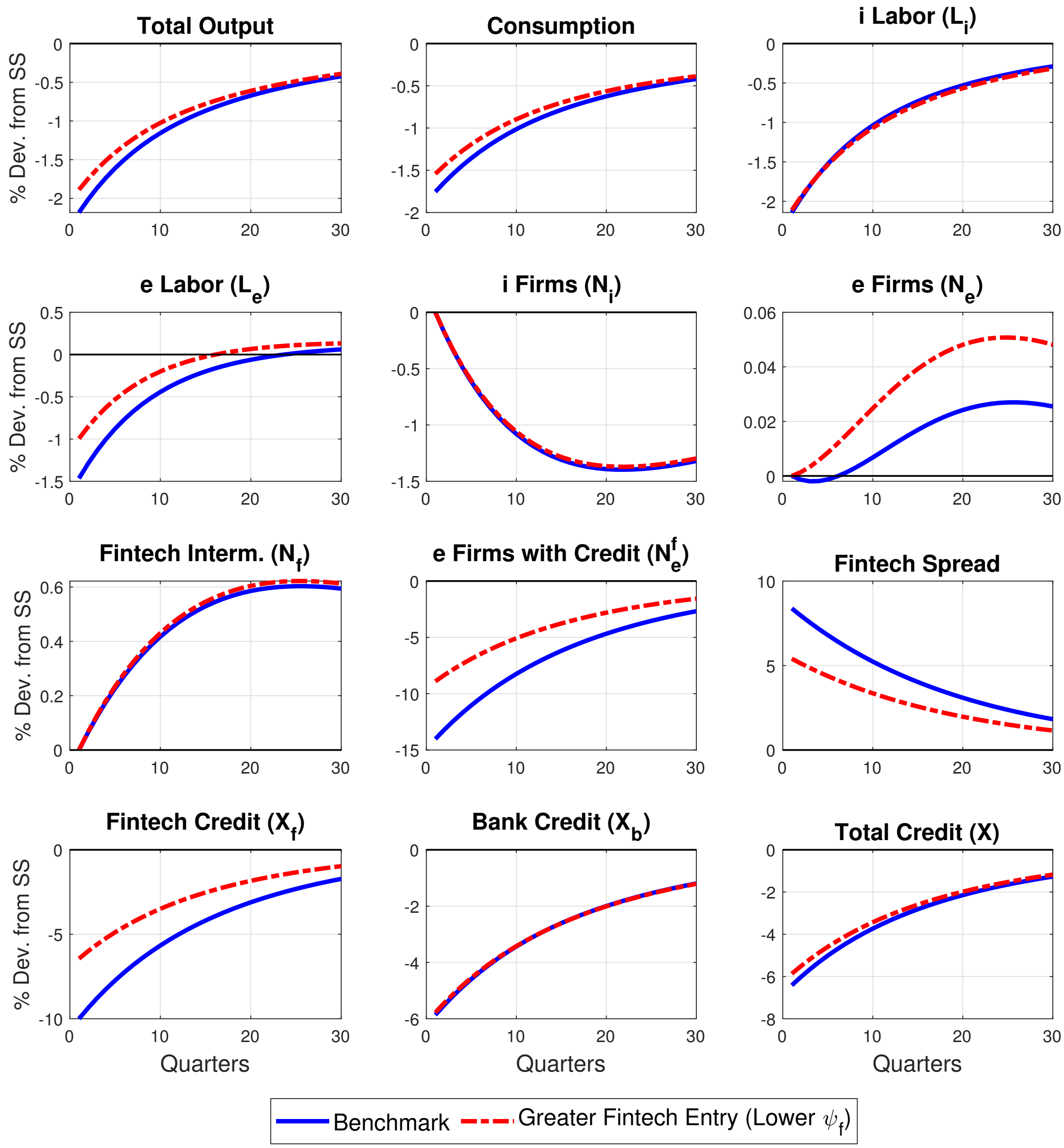


Figure A7: Response to a Temporary Adverse Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Model with Endogenous Bank and Fintech Intermediary Entry



A.2.7 Model with Endogenous Traditional-Bank Entry

Table A5: Steady-State Changes in Response to Greater Fintech Intermediary Entry (Reduction in ψ_f), Model with Endogenous Bank Entry and Oligopolistic Competition

	Benchmark Model Calibration (Lower ψ_f)	Model with Endogenous Traditional Bank Entry and Oligopolistic Compet. (Lower ψ_f)
Variable	**Change Relative to Baseline (% or PP)**	**Change Relative to Baseline (% or PP)**
Measure of Fintech Intermediaries N_f	52%	52%
Aggregate Output Y	0.48%	0.95%
Aggregate Consumption c	0.42%	1.23%
e-Firm Wage w_e	0.80%	1.92%
i-Firm Wage w_i	-0.37%	-0.84%
e Firms N_e	2.31%	5.18%
e Firms with Fintech Credit N_e^f	8.65%	20.57%
i Firms N_i	0.20%	0.20%
Traditional Banks B	–	0.07%
Aggregate Fintech Credit X_f	5.93%	13.94%
Aggregate Bank Credit X_b	-0.48%	-1.28%
Aggregate Credit X	0.23%	0.39%
Share of e Firms with Fintech Credit N_e^f/N_e	0.31 PP	0.73 PP
Total Share of Firms with Credit $\left(N_i + N_e^f\right)/N$	0.001 PP	0.02 PP
Ave. Fintech Lending Spread $\left(R_l^f - R_d^f\right)$	-3.96 PP	-9.17 PP
Ave. Bank Lending Spread $\left(R_l^b - R_d^b\right)$	–	-0.02 PP

Notes: $N \equiv (N_e + N_i)$ is the total measure of firms in the economy. All real variables are expressed in data-consistent terms unless otherwise noted. **PP denotes Percentage Points**.

Table A6: Changes in Business Cycle Volatility: Model with Endogenous Bank and Fintech Indermediary Entry under Oligopolistic Competition

Standard Deviations	**Baseline Model**	**Greater Fintech Entry (Lower ψ_f)**		**Greater Bank Entry (Lower ψ_b)**	
		SD	**Percent Change Relative to Benchmark**	**SD**	**Percent Change Relative to Benchmark**
$\sigma_{Y,t}$	3.10	2.77	**-10.65%**	2.50	**-19.29%**
$\sigma_{c,t}/\sigma_{Y,t}$	1.04	1.09	**4.81%**	1.12	**7.54%**
$\sigma_{inv,t}/\sigma_{Y,t}$	3.17*	3.35	**5.68%**	3.54	**11.75%**
$\sigma_{w_i,t}/\sigma_{Y,t}$	1.37	1.51	**10.22%**	0.91	**-33.72%**
$\sigma_{w_e,t}/\sigma_{Y,t}$	0.87	0.65	**-25.29%**	1.02	**17.55%**
$\sigma_{L_i,t}/\sigma_{Y,t}$	0.82	0.91	**10.98%**	0.51	**-37.38%**
$\sigma_{L_e,t}/\sigma_{Y,t}$	0.50	0.36	**-28.00%**	0.62	**23.98%**
$\sigma_{X_b,t}/\sigma_{Y,t}$	2.43*	2.68	**10.29%**	1.83	**-24.61%**
$\sigma_{X_f,t}/\sigma_{Y,t}$	3.08	1.52	**-50.65%**	3.79	**22.92%**
$\sigma_{X,t}/\sigma_{Y,t}$	2.49	2.53	**1.61%**	1.95	**-21.65%**

Notes: All real variables are expressed in data-consistent terms unless otherwise noted. To compute cyclical dynamics, we log-linearize the model and use a first-order approximation of the equilibrium conditions. We simulate the model for 2,000 periods and compute second moments using an HP filter with smoothing parameter 1600. A * denotes a targeted second moment. Percent changes in **blue** represent beneficial changes (volatility-wise) relative to the benchmark economy. Percent changes in **red** represent adverse changes (volatility-wise) relative to the benchmark economy.

Figure A8: Response to a Temporary Adverse Aggregate Productivity Shock, Model with Endogenous Bank and Fintech Intermediary Entry, Oligopolistic Competition

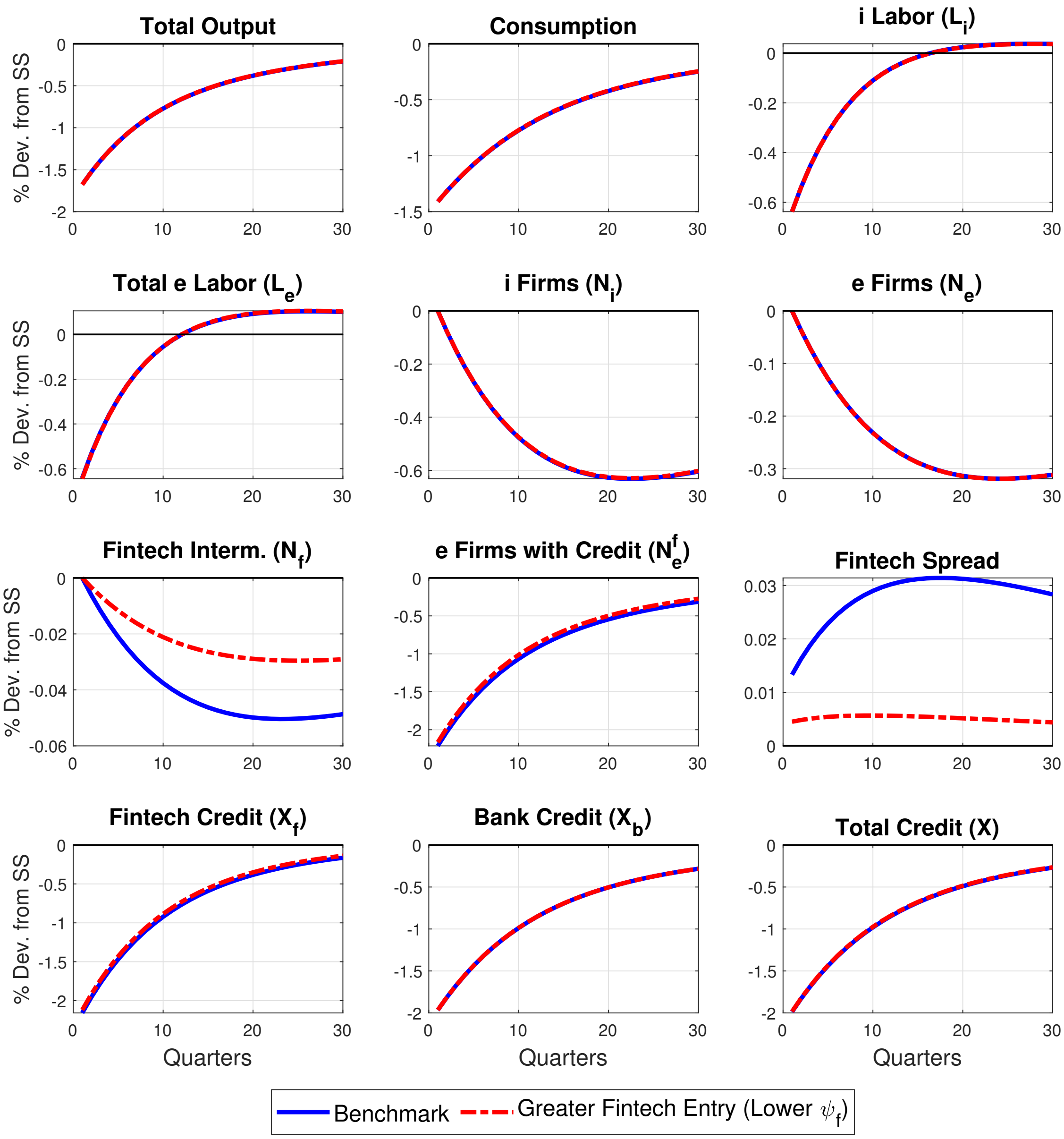


Figure A9: Response to a Temporary Adverse Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Model with Endogenous Bank and Fintech Intermediary Entry, Oligopolistic Competition