

Fintech Entry, Firm Financial Inclusion, and Macroeconomic Dynamics in Emerging Economies*

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January 18, 2022

Abstract

We build a model with a traditional banking system, endogenous entry of firms and fintech intermediaries, and firm heterogeneity in credit access and usage to study the credit-market, macroeconomic, and business cycle implications of the recent sizable growth in the number of fintech intermediaries in emerging economies. Our analysis delivers three findings. First, the impact of greater fintech entry on firm financial inclusion depends on whether greater entry is driven by lower entry costs for fintech intermediaries or lower barriers to fintech credit for unbanked firms. Second, greater fintech entry can have positive long-term macroeconomic effects. Third, greater fintech entry leads to a reduction in output volatility, but results in greater relative volatility in bank credit and consumption. The effects of fintech entry on macro outcomes and volatility hinge critically on the interaction between domestic financial shocks and the reduction in fintech lending rates stemming from greater fintech entry. Unless greater fintech entry leads to lower fintech credit costs for firms, greater fintech entry will have no meaningful credit-market or business cycle consequences.

JEL Classification: E24, E32, E44, F41, G21

Keywords: Financial access and participation, endogenous firm entry, banking sector, fintech entry, emerging economy business cycles

*We thank participants in the BCU-RIDGE 2021 Financial Stability Workshop for useful comments and feedback. The views in this paper are solely the responsibility of the authors and should not be interpreted as representing the views of the Federal Reserve Bank of Atlanta or Federal Reserve System, or the Inter-American Development Bank, its Executive Board, or its Management. Any errors are our own.

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1 Introduction

It is well known that firms in emerging economies (EMEs) face significant barriers to accessing formal credit, resulting in much lower shares of firms with credit—or lower firm financial inclusion—compared to advanced economies (Beck and Demirgüç-Kunt, 2006; Beck, Demirgüç-Kunt, and Martínez Pería, 2007; Epstein and Finkelstein Shapiro, 2021; Section 2). In recent years, growing levels of digital adoption by firms and the advent of financial technologies (fintech) have led to a rapid and dramatic increase in the number of fintech intermediaries, whose business model uses digital technologies to offer financial services—digital savings and payments, lending and credit provision via digital platforms—with lower barriers compared to traditional banks.

These developments have the potential to give small, unbanked firms—which represent a significant share of total employment and the bulk of firms in EMEs—access to formal credit (IFC, 2017; BIS, 2018, 2020; Sahay et al., 2020; Cantú and Ulloa, 2020). They also have the potential to reshape the domestic credit-market landscape by reallocating credit resources in an environment where traditional banks have been dominant. Understanding the impact of fintech on traditional banks is important from a macro standpoint: banks in EMEs not only account for the bulk of domestic credit, but they primarily cater to the larger, more productive firms, which are a major contributor to GDP even though they represent a very small share of the universe of firms in these economies. However, little is known about the implications of the growth in the number of fintech intermediaries for economy-wide firm financial inclusion, for the functioning and stability of the traditional banking system, and for credit-market and macroeconomic volatility in EMEs.

We provide a quantitative assessment of these implications by building a small-open-economy framework with costly creation of firms and fintech intermediaries and firm heterogeneity in access to credit. In the model, an endogenous sub-segment of firms uses credit from the traditional banking system and unbanked firms can choose to use fintech credit, leading to an endogenous share of firms that participate in credit markets. We calibrate the model to match key facts on firm financial inclusion, fintech intermediaries, and credit and macroeconomic dynamics in EMEs, and analyze the consequences of an increase in the

number of fintech intermediaries that is commensurate with the recent growth in the number of EME fintech intermediaries. In contrast to existing studies on fintech in EMEs, we look beyond the effects of fintech entry on long run aggregate outcomes and provide a first characterization of the implications for credit-market and macroeconomic dynamics.

Main Findings and Contributions Three main results emerge from our quantitative analysis. First, whether greater fintech entry increases the share of firms with formal credit (independent of source) or not depends on the root cause of this greater entry. While lower barriers to entry for fintech intermediaries—a supply-driven increase in the number of fintech intermediaries—do not change firm financial inclusion in the aggregate, lower barriers to accessing fintech credit for unbanked firms—a demand-driven increase in the number of fintech intermediaries—do increase firm financial inclusion. This result traces back to how greater fintech entry increases the number of firms that use fintech credit (a component of the numerator of firm financial inclusion), but also fosters greater firm entry across the board (the denominator of firm financial inclusion), thereby shaping equilibrium firm financial inclusion. Indeed, for the same increase in the number of fintech intermediaries, a reduction in the barriers that unbanked firms face in accessing fintech credit has stronger positive effects on the number of unbanked firms that adopt fintech credit, leading to greater firm financial inclusion.

Second, greater fintech entry can have positive long-term effects on consumption and GDP, an outcome that is in line with recent cross-country evidence (Sahay et al., 2020). Third, greater fintech entry leads to a reduction in output volatility, but to an increase in the relative volatility of consumption and bank credit. Importantly, this occurs because greater fintech entry has negligible quantitative effects on the responsiveness of firms that rely on bank credit, but leads to a more subdued response to domestic financial shocks by firms that use fintech credit that ultimately is powerful enough to reduce output volatility.

Further analysis reveals that the positive quantitative effects of fintech entry on long-run macro outcomes hinge critically on the endogenous reduction in average fintech lending rates stemming from greater fintech entry. In turn, the interaction between the reduction in fintech lending rates and domestic financial shocks plays a key role in explaining the changes

in business cycle volatility. This last finding has relevant policy implications for EMEs given the pace at which fintech intermediation has expanded in a very short time span: unless greater fintech entry leads to lower borrowing costs for firms that adopt fintech credit, greater fintech entry will have no meaningful credit-market and business cycle consequences.

Related Literature Our paper is primarily related to (1) the macro literature on endogenous firm entry, (2) growing work on the macroeconomic consequences of financial inclusion in EMEs, and (3) recent studies on the macroeconomic implications of digital adoption in these economies.

Our model builds on the well known endogenous firm entry framework by Bilbiie, Ghironi, and Melitz (2012) (BGM), which has been enriched along several dimensions, one of which is the inclusion of financial intermediation. For example, Stebunovs (2008) and Cacciatore, Ghironi, and Stebunovs (2015) analyze the macroeconomic consequences of changes in U.S. interstate banking competition in a model with firm creation where firms require bank credit upon entry. Totzek (2011) characterizes the business cycle effects of oligopolistic bank entry in the U.S. in a model with a fixed set of firms that adapts BGM to the banking sector. More recently, De Nicolò et al. (2021) study the cost of financial intermediation in the U.S. in a model that features bank entry and a choice by banks over IT adoption, where this choice shapes lending rates. These studies focus on the U.S. and therefore abstract from financial-inclusion considerations. In the context of EMEs, Barreto, Finkelstein Shapiro, and Nuguer (2021) study how domestic barriers to firm entry and firms' use of bank credit shape the propagation of foreign banking-sector shocks in EMEs. Their work focuses exclusively on the traditional banking system and does not address the role of fintech intermediaries in shaping credit market dynamics. The way we model the entry of fintech intermediaries is closest to Totzek (2011). We go a step further by incorporating endogenous firm entry and heterogeneous access to credit markets and sources, which are essential for our analysis of fintech and firm financial inclusion.

On the financial inclusion front, Dabla-Norris, Ji, Townsend, and Unsal (2021) use a framework with heterogeneity in financing constraints to 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 improvements in firm and household financial participation are critical for lowering aggregate volatility in EMEs and generating business cycle dynamics akin to those of advanced economies. While our framework also features firm heterogeneity in credit market participation, Epstein and Finkelstein Shapiro (2021) abstract from modeling the banking system and the possibility that financially-excluded firms can endogenously become financially included. Our framework incorporates a formal credit structure with traditional banks and the creation of fintech intermediaries where firms that enter the market without credit access can become financially included by choosing to use fintech credit. These features allow us to explicitly characterize the implications of fintech-led firm financial inclusion as well as the potential impact of greater fintech entry on the domestic banking system, including the implications for bank profits and bank-credit volatility.¹

Turning to work on digital adoption and 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 M-Pesa has large positive aggregate output effects. 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) study 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. Borrowing from this last paper, our model incorpo-

¹See Zhu (2021) for recent evidence on competition between fintech intermediaries and traditional banks in the deposit market in the context of China, and Suri et al. (2021) for empirical evidence on how fintech loans can make households more resilient to shocks in Kenya.

rates a costly digital adoption choice, which is a necessary condition for financially excluded firms to access to fintech credit in our context.

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 implications of fintech entry, we focus on a group of EMEs that has been extensively studied in the literature. This group is comprised of Argentina, Brazil, Chile, Colombia, Malaysia, Mexico, Peru, Philippines, South Africa, Thailand, and Turkey. These countries are among the select few outside of advanced economies that have business-cycle frequency data on bank credit, which allows us to readily discipline the volatility of credit in the baseline calibration of the model. Moreover, according to the Cambridge Center for Alternative Finance (CCAF), seven of these eleven EMEs—Argentina, Brazil, Chile, Colombia, Malaysia, Mexico, and the Philippines—are part of the top 20 lower- and upper-middle income economies with the highest per capita alternative finance—which fintech belongs to—volumes.

We first illustrate the prevalence of micro, small, and medium enterprises (MSMEs) in EMEs and their sizable contribution to total employment to highlight their importance as a key source of labor income. Then, 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 fraction of firms. This finance gap points to significant room for further domestic credit market development. Finally, we use available data to highlight the expansion of digital services and adoption—which is necessary for fintech—and summarize 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 most comprehensive 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. As is well known, the majority of firms in EMEs are informal and lack access to formal credit markets (IFC, 2010, 2013; column 8 of 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 fewer 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, the average MSME finance gap as a share of GDP—considering both formal and informal MSMEs—is sizable, especially when compared to average bank credit-GDP ratios in these economies (see columns 4, 5, and 6). Complementary survey data from the World Bank Enterprise Surveys (WBES) confirm the limited degree of firm participation in formal credit markets: on average, only 40 percent of formal firms in EMEs have a bank loan (column 7 of Table 1). While the same survey data also shows that roughly 40 percent of formal firms report not needing a loan, 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 participates in the banking system by using bank credit. Based on Table 1, 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

²The latest IFC data on MSMEs by formality status is only available until 2010. Thus, column 8 of Table 1, which shows the share of informal MSMEs, is only meant to highlight the breadth of firm informality in EMEs.

³Comparable 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.

universe of MSMEs.

To put the limited degree of firm financial participation in EMEs in perspective, consider the degree of firm financial participation in advanced economies, where MSMEs also account for the bulk of firms and, for firms that participate in formal credit markets, bank loans and credit lines are also the primary source of formal external financing. 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 improve firm access to formal credit in EMEs, especially for those firms that are currently not participating in the banking system. This 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 coverage varies by indicator and year. These limitations notwithstanding, Table 2 provides a snapshot of the recent evolution of digital adoption and fintech in these economies based on available data. As the table suggests, firms have steadily adopted digital technologies. In addition, the share of individuals with mobile money accounts, while low, has grown rapidly. Moreover, 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 expanded alongside mobile broadband subscriptions. Finally, the number of fintech firms, many of which provide digital and matching-based lending platforms to individuals and firms, has grown dramatically in recent years.⁴

⁴Examples of fintech firms in EMEs that offer digital payments and/or banking services, several of which compete with traditional banks, include 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 Internet		Number of Fintech Firms†		
		2014	2016	2014	2017	2014	2017	2017	2018	2017	2018	2017
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, IADB 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, in Latin American EMEs, the average number of fintech firms grew by 50 percent between 2017 and 2018 alone. For comparison, the average number of traditional commercial banks in EMEs has remained virtually unchanged since 2005 (IMF Financial Access Survey). As we describe below, the sharp expansion in the number of fintech firms has been accompanied by a dramatic rise in the volume of fintech credit as well (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), with firms using fintech credit primarily as working capital and to finance their investment expenditures (Claessens et al., 2018).⁵

Latin American EMEs (Argentina, Brazil, Chile, Colombia, Mexico, and Peru) provide the best snapshot of the characteristics, evolution, and growth of fintech in EMEs due to the relative availability of data on fintech characteristics for these economies. In particular, IADB (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 in the region, 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. Critically for our purposes and motivation, 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.⁶ Finally, while the latest data on digital adoption and fintech trends

⁵In many cases, the first experience of firms and their owners with fintech intermediaries is via the adoption of cashless payments and not credit. Fintech intermediaries then use information from firms' history of cashless payments to screen for potential borrowers, ultimately offering credit. For recent evidence on the link between cashless payments and fintech lending in an EME context, see Ghosh, Vallee, Zeng (2021).

⁶The 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

in EMEs is only available until 2018, Apedo-Amah et al. (2020) and CCAF, World Bank, and World Economic Forum (2020) note that the COVID-19 pandemic has only accelerated the pace of digital adoption in several EMEs.

3 The Model

The small open economy 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. Households are the ultimate owner of all firms, banks, and fintech intermediaries. They supply labor to firms and funds to finance bank and fintech-intermediary operations.

Total output is produced by two categories of monopolistically competitive firms—financially included (i) and excluded (e). Each category has an endogenous number of firms. Both e and i firms face sunk entry costs in the spirit of Bilbiie, Ghironi, and Melitz (2012) (BGM) and use labor supplied by households to produce (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 (proxied by the sunk entry costs they face); (2) their production technology upon entry; and (3) their participation (or lack thereof) in the traditional banking system through the use of bank credit. 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) as well as the sunk costs associated with i -firm creation (which can be interpreted as a form of investment; see BGM). In contrast, e firms face lower entry costs but enter the market without initially being able to access 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, formal firms in EMEs, which empirically account for the bulk of bank credit and tend to have better (more productive) production technologies, whereas e firms represent micro and small firms, which empirically face high barriers to participating in the banking system and tend to use more

percent, respectively.

precarious (and less productive) production technologies.⁷

To introduce the demand side of fintech credit, we assume that depending on the realized idiosyncratic productivity of e firms upon entry, a fraction of these firms are able to obtain loans offered by fintech intermediaries—fintech credit for short—and upgrade their production technology. However, obtaining fintech credit is possible only after incurring a fixed cost. 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 the production technology, among others. In this sense, the costly adoption of fintech credit can be considered a type of investment.⁸ We assume that fintech credit is used to finance a portion of firms’ wage bill and the fixed cost. Given this environment, only an endogenous sub-segment of e firms—those with high-enough productivity—ultimately decide to use fintech credit, which allows them to join the ranks of the financially included (see Beck et al., 2018, for more on the positive link between digital financial services and productivity).

The entry of fintech intermediaries is endogenous and subject to sunk costs. Given our interest in firm financial inclusion, we assume that fintech credit for firms is the sole financial service provided by these intermediaries. While fintech intermediaries tend to rely on a variety of funding sources—household deposits, venture capital, and/or equity issuance—we assume that funds supplied by households are the sole source of funds. Within the context of the model, these funds can be interpreted more broadly as any external funding used by fintech intermediaries to finance their operations. In contrast to fintech intermediaries, there is a fixed measure of traditional banks.⁹ Banks fund their lending operations to i firms

⁷Of note, to analyze how the entry of fintech intermediaries shapes formal credit markets in a transparent way, we abstract from modeling interfirm (input-based) trade credit, which is an important source of informal external finance for many EME firms, especially micro and small firms (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. Existing evidence also suggests that fintech-based digital loans need not replace other forms of existing credit (see Suri et al., 2021, for evidence from Kenya).

⁸Other 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.

⁹Appendices A.2.6 and A.2.7 present results for a version of the model modified to have endogenous bank entry. Of note, 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

using household funds. As such, traditional banks and fintech intermediaries compete for household funds.

Aggregate productivity, foreign interest rate, and domestic financial shocks generate business cycle fluctuations. The inclusion of domestic financial shocks allows us to replicate important features of credit market dynamics in EMEs.

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 in turn cater to an endogenous sub-segment 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 $Y_t = \left[\alpha_y \frac{1}{\phi_y} (Y_{i,t})^{\frac{\phi_y-1}{\phi_y}} + (1 - \alpha_y) \frac{1}{\phi_y} (Y_{e,t})^{\frac{\phi_y-1}{\phi_y}} \right]^{\frac{\phi_y}{\phi_y-1}}$, 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: $Y_{i,t} = \alpha_y (p_{i,t})^{-\phi_y} Y_t$ and $Y_{e,t} = (1 - \alpha_y) (p_{e,t})^{-\phi_y} Y_t$, 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

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.

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 function for a given firm ω_h 's output is given by

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

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 for $h \in \{e, i\}$. In what follows, we describe the problem of incumbent firms and delegate the description of the decisions over 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 a working capital loan from banks to cover a fraction $0 \leq \kappa_i \leq 1$ of its wage bill in advance, where the bank loan has a gross real interest rate $R_{l,t}^b$ and is repaid at the end of the same period. Thus, from firm ω_i 's perspective, the bank loan amount is $\kappa_i w_{i,t} l_{i,t}(\omega_i)$ where $w_{i,t}$ is the real wage. As noted in the general description of the model at the beginning of Section 3 and as we describe in the household's problem in Section 3.3, the sunk cost of creating i firms is also partially financed with bank credit. As such, the total bank loan amount will be greater than the relevant amount of i firms' total wage bill that is financed with bank credit.

Firm ω_i 's real profits in period t are given by

$$\pi_{i,t}(\omega_i) = \rho_{i,t}(\omega_i) y_{i,t}(\omega_i) - w_{i,t} l_{i,t}(\omega_i) + [\kappa_i w_{i,t} l_{i,t}(\omega_i) - R_{l,t}^b \kappa_i w_{i,t} l_{i,t}(\omega_i)].$$

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 $s \geq t$. 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 $mc_{i,t} = (1 - \kappa_i + \kappa_i R_{i,t}^b) w_{i,t}/z_{i,t}$ 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 into category i in period t , the evolution of i firms is given by $N_{i,t} = (1 - \delta)(N_{i,t-1} + H_{i,t-1})$, 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 a choice over fintech credit usage, we assume that upon entry, each e 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 $l_{e,t}^n(a_e)$ and produces $y_{e,t}^n(a_e) = z_{e,t}^n a_e l_{e,t}^n(a_e)$ where $z_{e,t}^n$ denotes the common exogenous productivity of those e firms that do not participate in credit markets. In turn, an e firm that enters the market and adopts fintech credit uses labor $l_{e,t}^f(a_e)$ and produces $y_{e,t}^f(a_e) = z_{e,t}^f a_e l_{e,t}^f(a_e)$, where $z_{e,t}^f$ denotes the exogenous common productivity of e firms that use fintech credit, where $z_e^n < z_e^f$. This assumption implies that, all else equal, e 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 the positive link between productivity and digital financial services). Even though $z_{e,t}^f$ and $z_{e,t}^n$ are exogenous, e firms still have an endogenous idiosyncratic productivity component that will ultimately determine e firms' equilibrium productivity and how many e 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 $\bar{a}_{e,t}$, the firm does not participate in credit

markets and its individual real profits are given by

$$\pi_{e,t}^n(a_e) = \rho_{e,t}^n(a_e)y_{e,t}^n(a_e) - w_{e,t}l_{e,t}^n(a_e),$$

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

$$\pi_{e,t}^f(a_e) = \rho_{e,t}^f(a_e)y_{e,t}^f(a_e) - w_{e,t}l_{e,t}^f(a_e) - R_{l,t}^f x_{f,t}(a_e) + x_{f,t}(a_e) - \psi_a,$$

where $\rho_{e,t}^f(a_e)$ 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 , where the fintech loan has a gross real interest rate $R_{l,t}^f$ and is repaid at the end of the period. Thus, from firm a_e 's perspective, the fintech loan amount is $x_{f,t}(a_e) = \kappa_e \left(w_{e,t}l_{e,t}^f(a_e) + \psi_a \right)$. Given the above conditions, it follows that an e firm is indifferent between not participating in credit markets and obtaining fintech credit when $\pi_{e,t}^n(\bar{a}_{e,t}) = \pi_{e,t}^f(\bar{a}_{e,t})$. This condition implicitly pins down the idiosyncratic productivity threshold level $\bar{a}_{e,t}$ 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 $\rho_{e,t}^n(a_e) = \left(\frac{\varepsilon}{\varepsilon-1} \right) \frac{mc_{e,t}^n}{a_e}$ and $\rho_{e,t}^f(a_e) = \left(\frac{\varepsilon}{\varepsilon-1} \right) \frac{mc_{e,t}^f}{a_e}$, respectively, where $mc_{e,t}^n = w_{e,t}/z_{e,t}^n$ and $mc_{e,t}^f = \left(1 - \kappa_e + \kappa_e R_{l,t}^f \right) w_{e,t}/z_{e,t}^f$ 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 $N_{e,t} = (1 - \delta)(N_{e,t-1} + H_{e,t-1})$. Of note, given the idiosyncratic productivity threshold level $\bar{a}_{e,t}$, we can separate the total mass of e firms into a mass that does not participate in credit

markets, $N_{e,t}^n = G(\bar{a}_{e,t})N_{e,t}$, and a mass that does via fintech credit, $N_{e,t}^f = [1 - G(\bar{a}_{e,t})]N_{e,t}$.

Firm Averages in Category e Given the presence of two sub-segments of e firms, we can define two average idiosyncratic productivity levels, one for each sub-segment. In particular, the average idiosyncratic productivity of e firms that do not participate in credit markets is $\tilde{a}_{e,t}^n = \left[\frac{1}{G(\bar{a}_{e,t})} \int_{a_{min}}^{\bar{a}_{e,t}} a_e^{\varepsilon-1} dG(a_e) \right]^{\frac{1}{\varepsilon-1}}$. In turn, the average idiosyncratic productivity of e firms that use fintech credit is $\tilde{a}_{e,t}^f = \left[\frac{1}{1-G(\bar{a}_{e,t})} \int_{\bar{a}_{e,t}}^{\infty} a_e^{\varepsilon-1} dG(a_e) \right]^{\frac{1}{\varepsilon-1}}$. We can then define average profits, average relative prices, and average output for the two sub-segments of e firms as follows: $\tilde{\pi}_{e,t}^n \equiv \pi_{e,t}^n(\tilde{a}_{e,t}^n)$ and $\tilde{\pi}_{e,t}^f \equiv \pi_{e,t}^f(\tilde{a}_{e,t}^f)$, $\tilde{\rho}_{e,t}^n \equiv \rho_{e,t}^n(\tilde{a}_{e,t}^n)$ and $\tilde{\rho}_{e,t}^f \equiv \rho_{e,t}^f(\tilde{a}_{e,t}^f)$, and $\tilde{y}_{e,t}^n \equiv y_{e,t}^n(\tilde{a}_{e,t}^n)$ and $\tilde{y}_{e,t}^f \equiv y_{e,t}^f(\tilde{a}_{e,t}^f)$. Finally, anticipating households' firm creation decisions in Section 3.3, we define average e -firm profits as $\pi_{e,t} = \left(\frac{N_{e,t}^n}{N_{e,t}} \right) \tilde{\pi}_{e,t}^n + \left(\frac{N_{e,t}^f}{N_{e,t}} \right) \tilde{\pi}_{e,t}^f$.

3.2 Financial Intermediation

There are two categories of financial intermediaries: traditional banks and fintech intermediaries. Both operate in a monopolistically competitive loan market and in a perfectly competitive deposit/funding market. Credit markets are segmented, with banks providing loans only to i firms and fintech intermediaries providing loans only to a sub-segment 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.¹⁰

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 $x_{b,t}(j) = X_{b,t} \partial R_{l,t}^b / \partial r_{l,t}^b(j)$ where $X_{b,t}$ denotes the total amount of bank loans to i firms, $r_{l,t}^b(j)$ is the real gross lending rate offered by bank j , and $R_{l,t}^b$ is the average real gross lending rate in the banking system. Each bank j sets its gross real lending rate $r_{l,t}^b(j)$ to

¹⁰Appendix A.2.6 presents results for a version of the model where bank entry is also endogenous and shows that our main findings remain unchanged.

maximize profits $\pi_{b,t}(j) = r_{l,t}^b(j)x_{b,t}(j) - R_{d,t}^b d_{b,t}(j)$, where $R_{d,t}^b$ 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 $x_{b,t}(j) = X_{b,t} \partial R_{l,t}^b / \partial r_{l,t}^b(j)$. Bank j 's first-order conditions deliver a standard markup over the deposit rate:

$$r_{l,t}^b(j) = \mu_{b,t} R_{d,t}^b, \quad (2)$$

where $\mu_{b,t}$ is the markup over the gross real deposit rate in the banking system. Under Dixit-Stiglitz loan aggregation, the demand for bank loans is $x_{b,t}(j) = (r_{l,t}^b(j)/R_{l,t}^b)^{-\varepsilon_{b,t}} X_{b,t}$ and the markup $\mu_{b,t} = \varepsilon_{b,t} / (\varepsilon_{b,t} - 1)$ 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

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 over fintech intermediary creation in the household's problem in Section 3.3.

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 $x_{f,t}(\zeta) = X_{f,t} \partial R_{l,t}^f / \partial r_{l,t}^f(\zeta)$, where $r_{l,t}^f(\zeta)$ is the real gross lending rate offered by fintech intermediary ζ , and $R_{l,t}^f$ is the average real gross lending rate in the fintech sector. An active fintech intermediary ζ has individual profits $\pi_{f,t}(\zeta) = r_{l,t}^f(\zeta)x_{f,t}(\zeta) - R_{d,t}^f d_{f,t}(\zeta)$, where $R_{d,t}^f$ is the common gross real rate on funds

$d_{f,t}(\zeta)$ supplied by households (the deposit rate), and a balance sheet constraint given by $x_{f,t}(\zeta) = d_{f,t}(\zeta)$.

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

$$r_{l,t}^f(\zeta) = \mu_{f,t} R_{d,t}^f, \quad (3)$$

where $\mu_{f,t}$ is the markup over the (common) gross real rate offered by fintech intermediaries to households for their funds. Under Dixit-Stiglitz aggregation, the demand for fintech loans is $x_{f,t}(\zeta) = \left(r_{l,t}^f(\zeta) / R_{l,t}^f \right)^{-\varepsilon_{f,t}} X_{f,t}$ where $\mu_{f,t} = \varepsilon_{f,t} / (\varepsilon_{f,t} - 1)$ is the lending markup and $\varepsilon_{f,t} > 1$ is the elasticity of substitution between fintech loans. We assume that $\varepsilon_{f,t}$ is subject to shocks that generate exogenous fluctuations in fintech lending spreads. Similar to the setup of banks, these shocks can also be 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 $N_{f,t} = (1 - \delta_f)(N_{f,t-1} + H_{f,t-1})$, 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 over the creation of i firms, e firms, and fintech intermediaries, taking all prices and individual profits as given. Moreover, as is standard in small open economy models, the household borrows from abroad.

Formally, the household chooses real consumption $c_{t,\text{total}}$ labor supply to i firms $L_{i,t,\text{total}}$ 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

$$c_t + D_{b,t} + D_{f,t} + (1 - \kappa_i + \kappa_i R_{l,t}^b) \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_f H_{f,t} + D_t^* + \frac{\eta^*}{2} (D_t^*)^2 = w_{i,t} L_{i,t} + w_{e,t} L_{e,t} \\ + R_{d,t-1}^b D_{b,t-1} + R_{d,t-1}^f D_{f,t-1} + S_{t-1} R_{t-1}^* D_{t-1}^* + \pi_{i,t} N_{i,t} + \pi_{e,t} N_{e,t} + \pi_{f,t} N_{f,t} + \pi_{b,t} B,$$

the evolution of i firms

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

the evolution of e firms

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

and the evolution of fintech intermediaries

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

where $u(c_t, L_{i,t}, L_{e,t})$ exhibits standard properties with respect to consumption and each category of labor, $D_{b,t} = \int_0^1 d_{b,t}(j) dj$, and $D_{f,t} = \int_{\zeta \in Z} d_{f,t}(\zeta) d\zeta$. Recall from the general description of the model at the beginning of Section 3 that firm creation is a form of investment, and that a fraction $0 \leq \kappa_i \leq 1$ of the sunk cost of creating i firms is financed with bank credit. Thus, if the sunk (resource) cost of creating one new i firm is ψ_i , the cost per new i firm inclusive of external financing costs is $(1 - \kappa_i + \kappa_i R_{l,t}^b) \psi_i$, where $R_{l,t}^b$ represents the real gross bank lending rate. Hence the term $(1 - \kappa_i + \kappa_i R_{l,t}^b) \psi_i H_{i,t}$ in the budget constraint, which represents the household's total resource cost of creating i firms. The term $(\eta^*/2) (D_t^*)^2$ 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.¹¹ The household's first-order conditions deliver standard

¹¹Given the relatively new nature of fintech, it is possible that providing 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 $R_{d,t}^b$ and $R_{d,t}^f$ but does not change any of our main conclusions.

Euler equations over bank deposits and fintech funds, $1 = \mathbb{E}_t \Xi_{t+1|t} R_{d,t}^b$ and $1 = \mathbb{E}_t \Xi_{t+1|t} R_{d,t}^f$, 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

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

and

$$\psi_i (1 - \kappa_i + \kappa_i R_{l,t}^b) = (1 - \delta) \mathbb{E}_t \Xi_{t+1|t} [\pi_{i,t+1} + \psi_i (1 - \kappa_i + \kappa_i R_{l,t+1}^b)], \quad (8)$$

and a fintech intermediary creation condition

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

where $\Xi_{t+1|t} \equiv \beta u_{c,t+1}/u_{c,t}$ is the household's stochastic discount factor. The intuition behind the Euler equations for bank deposits and fintech funds and optimal labor supply are 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 firms, 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:

$$r_{l,t}^f = N_{f,t}^{\frac{1}{\varepsilon_f - 1}} R_{l,t}^f, \quad (10)$$

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

$$r_{l,t}^b = B^{\frac{1}{\varepsilon_b-1}} R_{l,t}^b. \quad (12)$$

In turn, goods-market clearing implies that

$$Y_{i,t} = N_{i,t}^{\frac{\varepsilon}{\varepsilon-1}} y_{i,t}, \quad (13)$$

and

$$Y_{e,t} = \left(N_{e,t}^n (\tilde{y}_{e,t}^n)^{\frac{\varepsilon-1}{\varepsilon}} + N_{e,t}^f (\tilde{y}_{e,t}^f)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \quad (14)$$

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

$$L_{i,t} = l_{i,t} N_{i,t}, \quad (15)$$

and

$$L_{e,t} = N_{e,t}^n l_{e,t}^n + N_{e,t}^f l_{e,t}^f. \quad (16)$$

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

$$Y_t = c_t + \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_f H_{f,t} + \psi_a N_{e,t}^f + S_{t-1} R_{t-1}^* D_{t-1}^* + D_t^* + \frac{\eta^*}{2} (D_t^*)^2. \quad (17)$$

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 list of equilibrium conditions.

4 Quantitative Analysis

As is well known from BGM, “love for variety” is an inherent component of macro models with endogenous firm entry. However, 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 that includes this variety effect—call this non-adjusted, model-based real variable $o_{na,t}$ —and 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 $\Theta_t = \left(\alpha_y N_{i,t}^{\frac{1-\phi_y}{1-\varepsilon}} + (1 - \alpha_y) N_{e,t}^{\frac{1-\phi_y}{1-\varepsilon}} \right)$ purges the variety effect and is therefore readily comparable to its counterpart in the data. In what follows, all model-based real variables are expressed in data-consistent (or $o_{m,t}$) terms unless otherwise noted.

4.1 Calibration of Benchmark Economy

Functional Forms Section 3 presented several of the functional forms we adopt in our quantitative analysis. The 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 $u(c_t, L_{i,t}, L_{e,t}) = \frac{\left(c_t - Q_t \left(\gamma \frac{L_{e,t}^{1+\eta_e}}{1+\eta_e} + \gamma \frac{L_{i,t}^{1+\eta_i}}{1+\eta_i} \right) \right)^{1-\sigma}}{1-\sigma}$ 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). We also assume a Pareto distribution for $G(a_e) = 1 - \left(\frac{a_{min}}{a_e} \right)^{k_p}$ with shape parameter $k_p > \varepsilon - 1$ (Ghironi and Melitz, 2005). This functional form implies that the average idiosyncratic productivity levels for each sub-segment of e firms are given by $\tilde{a}_{e,t}^n = \tilde{a}_{e,t}^f \left(\frac{\frac{k_p - (\varepsilon - 1)}{a_{e,t}} - a_{min}^{k_p - (\varepsilon - 1)}}{\frac{k_p}{a_{e,t}} - a_{min}^{k_p}} \right)^{\frac{1}{\varepsilon - 1}} a_{min}$ and $\tilde{a}_{e,t}^f = \left(\frac{k_p}{k_p - (\varepsilon - 1)} \right)^{\frac{1}{\varepsilon - 1}} \bar{a}_{e,t}$.

Adjustment Costs Given the presence of 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 and allow us to capture empirically-consistent credit market fluctuations (for similar costs associated with the adjustment of capital and loans in a context with financial shocks, see, Iacoviello, 2015). Specifically, 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 $\phi_h (H_{e,t}/H_e - 1)^{\xi_e}$, $\phi_h (H_{i,t}/H_i - 1)^{\xi_i}$, and $\phi_h (H_{f,t}/H_f - 1)^{\xi_f}$ where $\xi_e, \xi_i, \xi_f > 1$, $\phi_h > 0$, and variables without time subscripts denote those same variables in steady state.

Shock Processes Following the EME literature, business cycles are driven by aggregate productivity shocks and foreign interest rate shocks. Moreover, as noted in Section 3, domestic financial shocks allow us to quantitatively match the volatility of bank credit in the data. 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-specific) domestic financial shock that affects average lending spreads across financial intermediaries. Following Neumeyer and Perri (2005) and related studies, we assume that the country spread is inversely related to expected aggregate productivity, $S_t = -\eta_s \mathbb{E}_t[Z_{t+1}]$, where parameter $\eta_s \geq 0$ dictates the strength of this inverse relationship and Z_t represents the aggregate component of sectoral productivities $z_{e,t}^n$, $z_{e,t}^f$, and $z_{i,t}$. The inclusion of country spreads allows us to match the countercyclicality of the trade balance, a well-known characteristic of EMEs. Finally, the gross real foreign interest rate follows an AR(1) process in logs with persistence parameter $0 < \rho_{R^*} < 1$ and shock $\nu_t^{R^*} \sim N(0, \sigma_{R^*})$.

Baseline Parameters from Literature A time period is a quarter. Following the EME literature, we set $\beta = 0.985$, $\sigma = 2$, $\delta = 0.025$, and $\gamma_c = 0.10$, 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). Following the macro literature on endogenous firm entry we normalize $a_{min} = 1$ and, as a baseline set assume $k_p = 4.2$, which satisfies the condition $k_p > \varepsilon - 1$. We choose $\phi_y = 5$, which allows for relatively high substitutability between

i and e output in total output (our results remain unchanged under alternative plausible values). 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 $\xi_i = \xi_e = \xi_f = 2$. Setting $\eta_e = \eta_i = 1.50$ delivers a Frisch elasticity of labor supply within the range considered plausible in the literature. Since we are primarily interested in the consequences of fintech entry, we normalize the fixed measure of banks to $B = 1$ without loss of generality. Based on evidence from IADB (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 $z_e^n = 1$ 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 Absent evidence suggesting otherwise, we assume that $\varepsilon_b = \varepsilon_f$ and, as a baseline *only*, that firms with credit (whether from banks or fintech intermediaries) have the same equilibrium average labor productivity. This assumption, which robustness checks confirm is innocuous and does not drive our main findings, is consistent with evidence on the positive link between productivity and access to credit and digital financial services (which, in our case, includes bank and fintech credit) (Dabla-Norris, Ho, and Kyobe, 2016; Beck et al., 2018).¹²

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 eleven first-moment targets based on available data for our EME sample or related EME studies. The 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

¹²To see what the resulting calibration target is, recall that e firms have both an endogenous productivity component reflected in \tilde{a}_e^f as well as an exogenous component reflected in z_e^f . Thus, the steady-state calibration target consistent with our assumption is $z_i = \tilde{a}_e^f z_e^f$.

total value added per available data from the OECD for EMEs with available data); 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 total time endowment (a standard target in the macro literature); an average share of firms with (bank and fintech) credit of 20 percent of the total measure of firms (consistent with IFC data for our EME sample); 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 equating the equilibrium average labor productivity of i firms and e firms with fintech credit.

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. This is important for analyzing how the entry of fintech intermediaries quantitatively affects the cyclical dynamics of bank and total credit. 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 $\phi_h = 0.0913$.

4.2 The Impact of Greater Fintech Entry

We consider two separate experiments that shed light on the macroeconomic and macro-financial implications of greater fintech entry. First, we analyze a reduction in the sunk entry cost of fintech intermediaries, ψ_f , holding all other parameters at their baseline values. This reduction encourages greater fintech 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 , holding all other parameters at their baseline values. This reduction in the fixed cost increases the demand for fintech credit by expanding the number of e firms that use such credit. This, in turn, encourages the entry of fintech intermediaries and results in an increase in N_f . To discipline these experiments, in each case, we reduce the corresponding cost—either ψ_f or ψ_a —so as to generate a 52-percent increase in the steady state measure of fintech intermediaries N_f , holding all other parameters at their baseline values.¹³ Per Table 2 in Section 2, the 52-percent increase in N_f matches the growth rate in the number of fintech intermediaries in EMEs between 2017 and 2018.

4.2.1 Steady State Changes

Main Results 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 entry obtained via a lower ψ_f (“Greater Fintech Entry via Lower ψ_f ,” column (2)), and in a version of the economy with greater fintech entry obtained via a lower ψ_a (“Greater Fintech Entry via Lower ψ_a ,” column (4)). The table also shows 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).

¹³It 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 that are at the margin of using fintech credit. Our baseline analysis abstracts from this link between costs so as 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 Entry (via Reduction in ψ_f or Reduction in ψ_a)

Variable	Baseline Economy	Greater Fintech Entry via Lower ψ_f	Change Relative to Baseline Economy (% or PP)	Greater Fintech 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 $(N_i + N_e^f)/N$	0.200*	0.200	0.001 PP	0.295	9.45 PP
Ave. Fintech Lending Spread $(R_l^f - R_d^f)$	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**. A * 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 in steady state, $R_d^f = 1/\beta$ is a constant, so the change in the fintech lending spread is driven by the change in the average fintech lending rate R_l^f .

As Table 3 illustrates, in both experiments, the steady state expansion in the measure of fintech intermediaries N_f leads an increase in total fintech credit X_f and to a reduction in the average fintech lending rate 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. As we discuss further below, the equilibrium change in fintech lending rates plays a key role in explaining the effects of greater fintech entry on long run macro outcomes and volatility.

Recall that the marginal cost of e firms that use fintech credit is $mc_e^f = \frac{(1-\kappa_e+\kappa_e R_l^f)w_e}{z_e^f \tilde{a}_e^f}$ 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 creation of e firms (reflected in greater N_e), to an increase in the measure of e firms that use fintech credit (reflected in greater N_e^f), to an increase in e labor (not shown), and to an increase in aggregate fintech credit (reflected in 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 in the baseline calibration generates a marginal increase in real i wages amid greater fintech entry. Regardless of the value of ϕ_y , though, greater fintech 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 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 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 —as well as consumption c and output Y are all greater in an economy with greater fintech entry, irrespective of the underlying reason for the increase in entry. 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 entry affects not only macroeconomic outcomes, but also the traditional banking sector (and the larger, more productive firms it caters to), firm creation across categories, and firm financial inclusion as measured by the share of firms with credit.

Table 3 shows two additional and important results. First, the increase in fintech 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, $(N_i + N_e^f) / N$, and therefore greater firm financial inclusion depends heavily on the quantitative change in the measure of e firms that use fintech credit. When greater fintech entry is rooted in a reduction in the sunk entry cost of fintech intermediaries, the share $(N_i + N_e^f) / N$ remains for all intents and purposes unchanged relative to its baseline of 20 percent. In other words, the dramatic expansion in fintech entry has no quantitatively meaningful impact on firm financial inclusion.¹⁴ In contrast, when greater fintech entry is demand-driven and rooted in e firms finding easier to access fintech credit (via a reduction in ψ_a), the share $(N_i + N_e^f) / N$ expands by almost 10 percentage points (from 0.20 to 0.295). 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, which stem from the larger increase in the total number of firms in the economy.

Driving Forces and Mechanisms There are two main mechanisms via which greater fintech entry affects steady-state credit-market and macroeconomic outcomes: (1) a change in e firms’ endogenous productivity component as a larger sub-segment of e firms takes on fintech credit, and (2) an endogenous reduction in average fintech lending rates as more fintech intermediaries enter the market. In turn, these two mechanisms interact with the economy’s shocks and shape credit-market and aggregate fluctuations, as we discuss in Section 4.2.2.

To determine which mechanism dominates quantitatively, we consider two steady-state experiments.

¹⁴Of note, were we to hold the total number of e firms at its baseline value, $(N_i + N_e^f) / N$ would increase by 0.34 percentage points to 20.34 percent, which is still a negligible change considering the sharp growth in the number of fintech intermediaries.

Table 4: Steady State Changes in Response to Greater Fintech Entry (via Reduction in ψ_f), Fixed e -Firm Productivity vs. Fixed Fintech Lending Rates

Variable	(1)	(2)	(3)
	Change Relative to Baseline Economy (% or PP), Lower ψ_f	Change Relative to Baseline Economy (% or PP), Lower ψ_f Holding \tilde{a}_e^f (and \tilde{a}_e^n) at Baseline	Change Relative to Baseline Economy (% or PP), Lower ψ_f Holding Fintech Lending Rate at Baseline
Measure of Fintech Intermediaries N_f	52%	52%	52%
Aggregate Output Y	0.48%	0.37%	0.09%
Aggregate Consumption c	0.42%	0.33%	-0.07%
e -Firm Wage w_e	0.80%	0.65%	0.00%
i -Firm Wage w_i	-0.37%	-0.23%	0.00%
Measure of e Firms N_e	2.31%	1.51%	0.14%
Measure of e Firms with Fintech Credit N_e^f	8.65%	1.51%	0.14%
Measure of i Firms N_i	0.20%	0.19%	0.14%
Aggregate Fintech Credit X_f	5.93%	4.24%	0.09%
Aggregate Bank Credit X_b	-0.48%	-0.26%	0.09%
Aggregate Credit X	0.23%	0.23%	0.09%
Share of e Firms with Fintech Credit N_e^f/N_e	0.31 PP	0.00 PP	0.00 PP
Share of Firms with Credit $(N_i + N_e^f)/N$	0.001 PP	-0.17 PP	0.00 PP
Ave. Fintech Lending Spread $(R_l^f - R_d^f)$	-3.96 PP	-3.96 PP	0.00 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.** A * 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 in steady state, $R_d^f = 1/\beta$ is a constant, so the change in the fintech lending spread is driven by the change in the average fintech lending rate R_l^f .

The first experiment consists of reducing ψ_f to generate the 52 percent increase in the measure of fintech intermediaries while simultaneously changing ψ_a so as to keep the endogenous productivity components of e firms (\tilde{a}_e^f and \tilde{a}_e^n) unchanged at their baseline steady-state values.¹⁵ The second experiment consists of reducing ψ_f to generate the same percent increase in the measure of fintech intermediaries while simultaneously changing ε_f so as to keep the average fintech lending rate (R_l^f , and therefore the average fintech lending spread, $R_l^f - R_d^f$) unchanged at its baseline steady-state value.

The results from the first and second experiments are presented in columns (2) and (3), respectively, of Table 4. For comparability, column (1) of the same table replicates the steady state results from column (3) of Table 3. The results in Table 4 clearly show that the reduction in average fintech lending rates induced by greater average fintech entry is the main driver of the positive effects of fintech entry on credit-market and macro outcomes. We revisit this important result in the context of the model’s cyclical dynamics below.

4.2.2 Cyclical Volatility

Main Results Table 5 compares the unconditional volatility of key variables in the benchmark economy (column (1)) and in the economy with greater fintech entry for the same two scenarios analyzed in Section 4.2.1 (that is, greater entry via a lower ψ_f , shown in column (2) of Table 5, or via a lower ψ_a , shown in column (4) of the same table, as well as their respective percent-change comparisons with the benchmark economy, shown in column (3) for the reduction in ψ_f and in column (5) for the reduction in ψ_a).¹⁶

¹⁵Changing ψ_a affects the endogenous idiosyncratic threshold \bar{a}_e . In turn, as noted in Section 4.1, the value of \bar{a}_e simultaneously determines the equilibrium values of both \tilde{a}_e^f and \tilde{a}_e^n .

¹⁶Of note, the benchmark model generates a relative volatility of the *average* real wage in the economy (not shown) 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, which is a well-known characteristic of EME business cycles). This limitation, 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 of our baseline analysis (see Tables A4 and A6 in Appendix A.2).

Table 5: Changes in Business Cycle Volatility: Benchmark Economy and Economy with Greater Fintech Entry (via Reduction in ψ_f or Reduction in ψ_a)

Standard Deviations	Benchmark Economy	Greater Fintech Entry			
	(1)	(2)	(3)	(4)	(5)
		Via Lower ψ_f	Percent Change (2) Relative to (1)	Via Lower ψ_a	Percent Change (4) Relative to (1)
$\sigma_{Y,t}$	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. 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.

An increase in the average measure of fintech intermediaries reduces the volatility of output ($\sigma_{Y,t}$), the relative volatility of labor and real wages of 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 and wages of i firms ($\sigma_{L_i,t}/\sigma_{Y,t}$ and $\sigma_{w_i,t}/\sigma_{Y,t}$), and increases the relative volatility of consumption ($\sigma_{c,t}/\sigma_{Y,t}$) and bank credit ($\sigma_{X_b,t}/\sigma_{Y,t}$) (while not shown, the cyclical of the trade balance-output ratio remains virtually unchanged). We note, though, that the increase in relative volatilities is driven solely by the quantitative reduction in output volatility as opposed to an increase in the absolute volatility of the other variables.

All told, greater fintech entry generates asymmetric changes in volatility across firm

categories, ultimately leading to an increase in the relative volatility of consumption and bank credit. More broadly, the results in Table 5 imply that the expansion in fintech intermediaries can have an outsized influence on bank and aggregate credit, as well as macroeconomic dynamics. These findings are particularly noteworthy because, even after the sharp increase in the average measure of fintech intermediaries, bank credit continues to represent roughly 85 percent of total credit.

Similar to the results in Table 3, the underlying source of the increase in the average measure of fintech intermediaries shapes the *quantitative* change in relative volatilities and, in the case of aggregate credit and investment *only*, 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 the case where the increase in fintech intermediaries is rooted in a lower ψ_a . This, in turn, explains the larger changes in relative volatilities stemming from 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 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 fintech intermediaries, the contribution of fintech credit to aggregate credit is larger (see Table 3). The larger reduction in the relative volatility of fintech credit and the more subdued increase in the relative volatility of bank credit explain the reduction in the relative volatility of aggregate credit ($\sigma_{X_t}/\sigma_{Y,t}$) when the entry of fintech intermediaries is demand-driven.

Driving Forces: The Role of Domestic Financial Shocks Table 5 focused solely on changes in unconditional volatility. A cursory look at the impulse responses for each of these shocks makes clear that the main driver of the changes in relative volatility in Table 5 is the differential response of the economy to domestic financial shocks. Indeed, greater average fintech entry does not generate a discernible differential effects on credit market and macro variables in response to aggregate productivity or foreign interest rate shocks (see Figure A1 in Appendix A.2.1 and Figure A2 in Appendix A.2.2). Given these results, we focus on the response to domestic financial shocks.

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

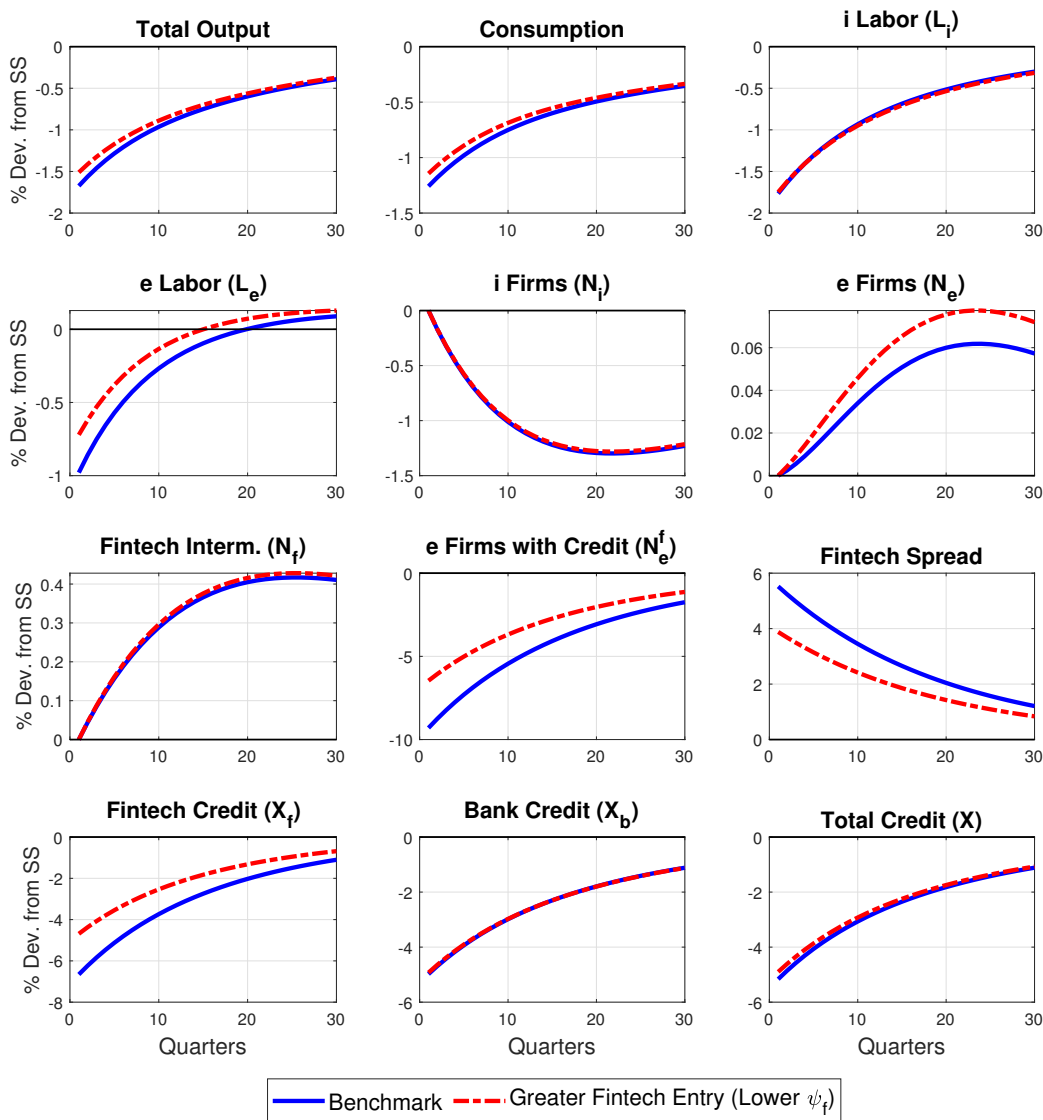


Figure 1 plots the responses of the benchmark economy (solid blue line) and the economy amid greater average fintech entry (without loss of generality, stemming from a lower ψ_f ; dash-dotted red line) to an identical one-standard-deviation temporary adverse aggregate domestic financial shock (i.e., a joint reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$ that induces a temporary and simultaneous increase in bank and fintech lending rates; recall that domestic financial shocks allow the benchmark model to replicate the relative volatility of bank credit in our EME

sample).

In response to the shock, the economy with greater average fintech entry exhibits a more subdued contraction in total output. 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 entry reduces the average lending rate (and associated lending spread) for the subset of e firms that decide to use fintech credit in the steady state. As such, for a given adverse domestic financial shock, the shock-induced increase in fintech lending rates (which all else equal raises lending spreads and financial intermediaries' profits, and explains the expansion of fintech intermediaries) is smaller amid greater average fintech 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 fintech borrowing 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.

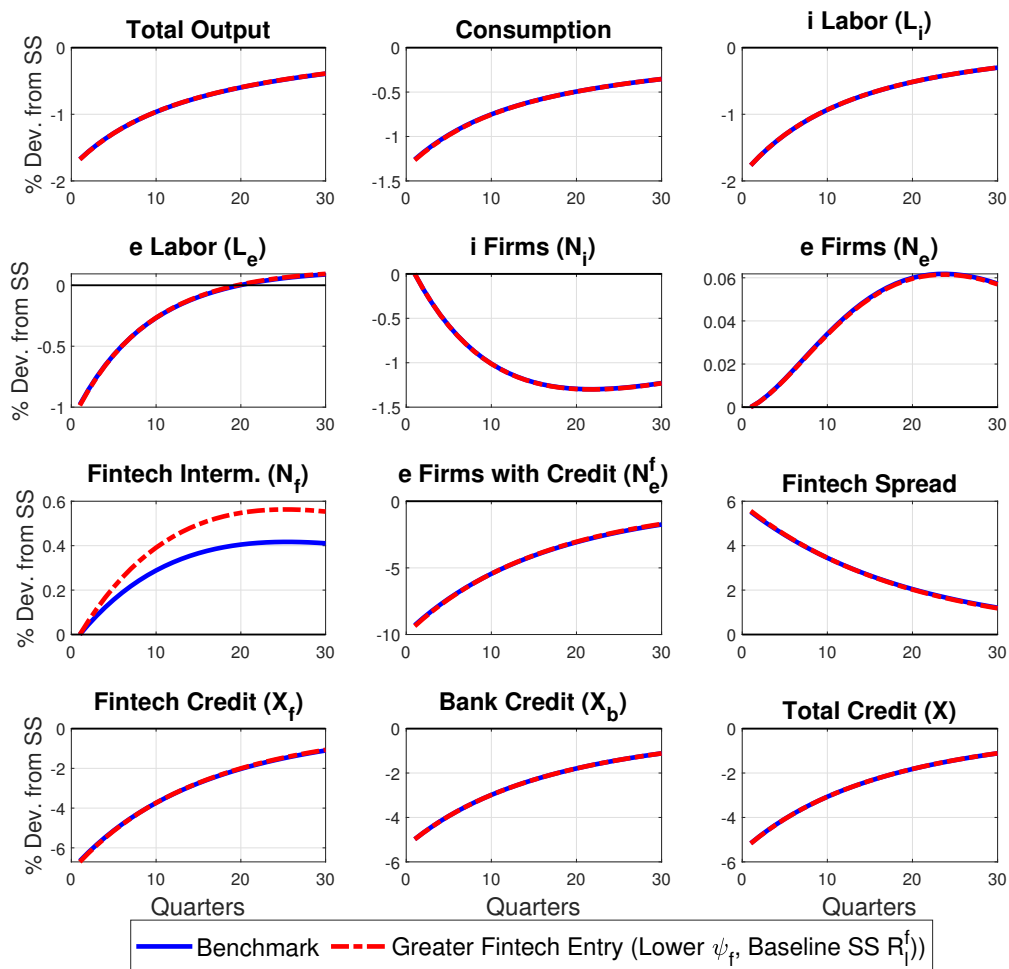
The smaller contraction in the measure of e firms with fintech credit, coupled with the fact that e firms without credit are not directly impacted by the domestic financial shock, further limits the contraction in total e labor, thereby stabilizing household income (not shown). Turning to i firms, since domestic financial shocks affect 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 does not meaningfully change (this result continues to hold when we allow for endogenous movements in the measure of traditional banks; see Appendices A.2.6 and A.2.7).

All told, despite the fact that e firms with fintech credit account 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 entry is powerful enough to limit the contraction in total output in response to adverse domestic financial shocks. This, in turn, implies that *relative to the response of total output*, i -firm variables remain more responsive to domestic financial shocks under greater fintech entry. Hence the

increase in the relative volatility of bank and aggregate credit, investment, and i -firm labor and wages shown in column (3) of Table 5.

Changes in Average Fintech Lending Rates and Domestic Financial Shocks The endogenous reduction in the steady-state average fintech lending rate highlighted in Section 4.2.1 plays a pivotal role in generating differential dynamics in response to domestic financial shocks, and therefore in explaining the volatility results in Table 5.

Figure 2: Response to a Temporary Adverse Domestic Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Holding Average Fintech Lending Rate R_t^f at its Baseline Steady-State Value



This is confirmed by Figure 2, which shows the response to an adverse domestic financial shock when we increase the average measure of fintech intermediaries while simultaneously

changing the steady state value of ε_f so as to keep the average fintech lending rate R_l^f at its baseline steady-state value.

Indeed, when the average fintech lending rate is kept at its baseline steady-state value, an increase in the average measure of fintech intermediaries does not meaningfully change the response of credit-market and macro variables to domestic financial shocks (the same claim applies to the response to other shocks). The intuition for this result is simple: without a change in the cost of fintech credit, which as described earlier plays a key role in shaping the marginal cost of e firms with fintech credit, the sensitivity of these firms to domestic financial shocks does not change in a meaningful way. Hence the absence of a differential response to shocks in Figure 2.

4.2.3 Additional Results and Robustness Analysis

Macro and Credit Market Volatility from Fintech vs. Bank Entry A natural question is whether an increase in total credit stemming from an increase in the measure of traditional banks has similar consequences for credit 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 that we obtain under greater average fintech entry (via a reduction in ψ_f). 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 ; originally shown in column (3) of Table 5).¹⁷ Qualitatively, both a greater average 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 entry generates a larger increase in relative volatility across a host of variables. This finding points to the

¹⁷To confirm that the results in Table A1 are robust, we also conduct the same experiment in versions of the benchmark model that incorporate 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).

importance of the composition of total credit, and the implications of this composition for credit market volatility in a context with fintech entry.

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 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. Relatedly, 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.

Fintech Entry Costs and Foreign Interest Rate Shocks Assuming that the sunk cost of fintech 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 average fintech entry as those in the benchmark model (results available upon request). These results suggest that it is indeed disturbances in domestic credit markets that drive the change in cyclical credit and macroeconomic dynamics as a result of greater average fintech entry.

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 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’ steady-state gross deposit interest rates a function of deposits and allows changes in these deposits—say, due to an increase in fintech 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 average fintech 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 Bank Entry and Oligopolistic Competition in Credit Markets Table A3 and Figures A6 and A7 in Appendix A.2 show that our main findings continue to hold when we allow for endogenous bank entry alongside fintech entry. In fact, our main quantitative results become somewhat stronger when bank entry is endogenous.

Assuming monopolistically competitive credit markets with Dixit-Stiglitz preferences implies that the lending-deposit spreads of traditional banks and individual fintech intermediaries are a constant markup over the deposit rate.¹⁸ Introducing oligopolistic competition between 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. This alternative assumption does not change our main conclusions, even if we assume endogenous bank entry as well (see Table A5 and Figures A8 and A9 of Appendix A.2).¹⁹

5 Conclusion

Compared to advanced economies, emerging economies (EMEs) have considerably lower levels of firm financial inclusion as reflected in a larger fraction of firms that are excluded from the traditional banking system. These firms account for a large share of total employment and represent a significant fraction of the universe of firms.

In recent years, the steady adoption of digital technologies in EMEs has been accompanied by the emergence and dramatic expansion in the number of fintech intermediaries—non-traditional financial intermediaries whose business model leverages the use of digital technologies to provide financial services to firms and individuals. Many of these intermediaries have focused on firms that face high barriers to participating in the domestic

¹⁸Of note, the average fintech lending rate, R_l^f , depends on both the average individual fintech lending rate r_l^f and the measure of fintech intermediaries N_f . As such, R_l^f can change in response to fintech entry.

¹⁹For 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 Toltzek (2011), who adapts the goods-sector endogenous entry setup in Colciago and Etro (2011) to the banking sector.

banking system. The rapid growth in the number of fintech intermediaries in EMEs, coupled with the fact that fintech intermediaries may compete for resources with traditional banks, raises important questions about the consequences of this growth for firm financial inclusion, credit market and macroeconomic outcomes, and cyclical credit and aggregate dynamics. We propose a framework with a traditional banking system, the endogenous creation of fintech intermediaries, endogenous firm entry, and firm heterogeneity. In the model, firms differ in their access to and source of credit, and the economy's degree of firm financial inclusion is endogenous. Calibrating the model to match key characteristics of EME bank-credit and macroeconomic dynamics, we quantitatively characterize the financial inclusion, credit-market, and business cycle implications of greater fintech entry.

Our quantitative analysis deliver three main results. First, the effects of greater fintech entry on firm financial inclusion depend on the root cause of this greater entry: lower entry barriers for fintech intermediaries—a supply-driven expansion—do not change firm financial inclusion in the aggregate, whereas lower barriers to accessing fintech credit by firms—a demand-driven expansion—do. Second, greater fintech entry can have positive long-term macroeconomic effects. Third, greater fintech entry leads to a reduction in output volatility that is driven by the more subdued response of firms that use fintech credit to domestic financial shocks, but has negligible effects on the behavior of firms that rely on bank credit. As a result, greater fintech entry is reflected in greater relative volatility in bank credit and consumption. Importantly, further analysis reveals that the effects of fintech entry on long-run macro outcomes and volatility hinge critically on the reduction in fintech lending rates stemming from greater fintech entry. Our findings have broader policy implications: unless greater fintech entry leads to lower borrowing costs for firms that adopt fintech credit, an expansion the number of fintech intermediaries will have no meaningful credit-market and business cycle consequences in EMEs.

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A Online Appendix

A.1 Equilibrium Conditions: Benchmark Model

Taking the stochastic processes $\{z_{i,t}, z_{e,t}^n, z_{e,t}^f, \varepsilon_{b,t}, \varepsilon_{f,t}\}$ as given, the allocations and prices $\{Y_t, Y_{i,t}, Y_{e,t}\}$, $\{y_{i,t}, l_{e,t}^n, l_{e,t}^f, n_{i,t}, c_t, R_{d,t}^b, R_{d,t}^f, d_{f,t}, L_{i,t}, L_{e,t}, H_{e,t}, H_{i,t}, \pi_{e,t}, H_{f,t}, N_{i,t}, N_{e,t}, N_{f,t}\}$, and $\{R_{l,t}^b, R_{l,t}^f, \rho_{i,t}, \tilde{\rho}_{e,t}^n, \tilde{\rho}_{e,t}^f, N_{e,t}^f, \bar{a}_{e,t}, \tilde{a}_{e,t}^n, \tilde{a}_{e,t}^f, \tilde{\pi}_{e,t}^n, \tilde{\pi}_{e,t}^f, \tilde{y}_{e,t}^n, \tilde{y}_{e,t}^f, w_{i,t}, w_{e,t}, r_{l,t}^b, r_{l,t}^f, p_{e,t}, p_{i,t}, \rho_{e,t}, D_{f,t}, D_t^*\}$ satisfy:

$$Y_t = \left[\alpha_y^{\frac{1}{\phi_y}} (Y_{i,t})^{\frac{\phi_y-1}{\phi_y}} + (1 - \alpha_y)^{\frac{1}{\phi_y}} (Y_{e,t})^{\frac{\phi_y-1}{\phi_y}} \right]^{\frac{\phi_y}{\phi_y-1}}, \quad (18)$$

$$Y_t = c_t + \psi_i H_{i,t} + \psi_e H_{e,t} + \psi_f H_{f,t} + \psi_a N_{e,t}^f + S_{t-1} R_{t-1}^* D_{t-1}^* + D_t^* + \frac{\eta^*}{2} (D_t^*)^2, \quad (19)$$

$$Y_{i,t} = N_{i,t}^{\frac{\varepsilon}{\varepsilon-1}} y_{i,t}, \quad (20)$$

$$Y_{e,t} = \left(N_{e,t}^n (\tilde{y}_{e,t}^n)^{\frac{\varepsilon-1}{\varepsilon}} + N_{e,t}^f (\tilde{y}_{e,t}^f)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \quad (21)$$

$$y_{i,t} = z_{i,t} l_{i,t}, \quad (22)$$

$$L_{e,t} = N_{e,t}^n l_{e,t}^n + N_{e,t}^f l_{e,t}^f, \quad (23)$$

$$L_{i,t} = l_{i,t} N_{i,t}, \quad (24)$$

$$1 = \mathbb{E}_t \Xi_{t+1|t} R_{d,t}^b, \quad (25)$$

$$1 = \mathbb{E}_t \Xi_{t+1|t} R_{d,t}^f, \quad (26)$$

$$1 = \mathbb{E}_t \Xi_{t+1|t} S_t R_t^* + \eta^* (D_t^*), \quad (27)$$

$$D_{f,t} = \kappa_e \left(w_{e,t} n_{e,t}^f + \psi_a \right) N_{e,t}^f, \quad (28)$$

$$-u_{L_{i,t}} = w_{i,t} u_{c,t}, \quad (29)$$

$$-u_{L_{e,t}} = w_{e,t} u_{c,t}, \quad (30)$$

$$\psi_e = (1 - \delta) \mathbb{E}_t \Xi_{t+1|t} [\pi_{e,t+1} + \psi_e], \quad (31)$$

$$\psi_i (1 - \kappa_i + \kappa_i R_{l,t}^b) = (1 - \delta) \mathbb{E}_t \Xi_{t+1|t} \left[\left(\rho_{i,t+1} - \frac{(1 - \kappa_i + \kappa_i R_{l,t+1}^b) w_{i,t+1}}{z_{i,t+1}} \right) y_{i,t+1} \right], \quad (32)$$

$$+ (1 - \delta) \mathbb{E}_t \Xi_{t+1|t} [\psi_i (1 - \kappa_i + \kappa_i R_{l,t+1}^b)]$$

$$\pi_{e,t} = \left(\frac{N_{e,t} - N_{e,t}^f}{N_{e,t}} \right) \tilde{\pi}_{e,t}^n + \left(\frac{N_{e,t}^f}{N_{e,t}} \right) \tilde{\pi}_{e,t}^f, \quad (33)$$

$$\psi_f = (1 - \delta_f) \mathbb{E}_t \Xi_{t+1|t} \left[\left(r_{l,t+1}^f - R_{d,t+1}^f \right) d_{f,t+1} + \psi_f \right], \quad (34)$$

$$N_{i,t+1} = (1 - \delta)(N_{i,t} + H_{i,t}), \quad (35)$$

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

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

$$r_{l,t}^b = \mu_{b,t} R_{d,t}^b, \quad (38)$$

$$r_{l,t}^f = \mu_{f,t} R_{d,t}^f, \quad (39)$$

$$\rho_{i,t} = \left(\frac{\varepsilon}{\varepsilon - 1} \right) \frac{(1 - \kappa_i + \kappa_i R_{l,t}^b) w_{i,t}}{z_{i,t}}, \quad (40)$$

$$\tilde{\rho}_{e,t}^n = \left(\frac{\varepsilon}{\varepsilon - 1} \right) \frac{w_{e,t}}{z_{e,t}^n \tilde{a}_{e,t}^n}, \quad (41)$$

$$\tilde{\rho}_{e,t}^f = \left(\frac{\varepsilon}{\varepsilon - 1} \right) \frac{(1 - \kappa_e + \kappa_e R_{l,t}^f) w_{e,t}}{z_{e,t}^f \tilde{a}_{e,t}^f}, \quad (42)$$

$$N_{e,t}^f = [1 - G(\bar{a}_{e,t})] N_{e,t}, \quad (43)$$

$$\pi_{e,t}^n(\bar{a}_{e,t}) = \pi_{e,t}^f(\bar{a}_{e,t}), \quad (44)$$

$$\tilde{a}_{e,t}^n = \tilde{a}_{e,t}^f \left(\frac{\bar{a}_{e,t}^{k_p - (\varepsilon - 1)} - a_{min}^{k_p - (\varepsilon - 1)}}{\bar{a}_{e,t}^{k_p} - a_{min}^{k_p}} \right)^{\frac{1}{\varepsilon - 1}} a_{min}, \quad (45)$$

$$\tilde{a}_{e,t}^f = \left(\frac{k_p}{k_p - (\varepsilon - 1)} \right)^{\frac{1}{\varepsilon - 1}} \bar{a}_{e,t}, \quad (46)$$

$$\tilde{\pi}_{e,t}^n = \left(\tilde{\rho}_{e,t}^n - \frac{w_{e,t}}{z_{e,t} \tilde{a}_{e,t}^n} \right) \tilde{y}_{e,t}^n, \quad (47)$$

$$\tilde{\pi}_{e,t}^f = \left(\tilde{\rho}_{e,t}^f - \frac{w_{e,t} (1 - \kappa_e + \kappa_e R_{l,t}^f)}{z_{e,t} \tilde{a}_{e,t}^f} \right) \tilde{y}_{e,t}^f - \psi_a (1 - \kappa_e + \kappa_e R_{l,t}^f), \quad (48)$$

$$\tilde{y}_{e,t}^n = z_{e,t}^n \tilde{a}_{e,t}^n l_{e,t}^n, \quad (49)$$

$$\tilde{y}_{e,t}^f = z_{e,t}^f \tilde{a}_{e,t}^f l_{e,t}^f, \quad (50)$$

$$Y_{i,t} = \alpha_y (p_{i,t})^{-\phi_y} Y_t, \quad (51)$$

$$Y_{e,t} = (1 - \alpha_y) (p_{e,t})^{-\phi_y} Y_t, \quad (52)$$

$$\tilde{y}_{e,t}^n = \left(\frac{\tilde{\rho}_{e,t}^n}{p_{e,t}} \right)^{-\varepsilon} Y_{e,t}, \quad (53)$$

$$\tilde{y}_{e,t}^f = \left(\frac{\tilde{\rho}_{e,t}^f}{p_{e,t}} \right)^{-\varepsilon} Y_{e,t}, \quad (54)$$

$$r_{l,t}^f = N_{f,t}^{\frac{1}{\varepsilon_f - 1}} R_{l,t}^f, \quad (55)$$

$$r_{l,t}^b = B_{e,t}^{\frac{1}{\varepsilon_b - 1}} R_{l,t}^b, \quad (56)$$

$$p_{i,t} = N_{i,t}^{\frac{1}{1-\varepsilon}} \rho_{i,t}, \quad (57)$$

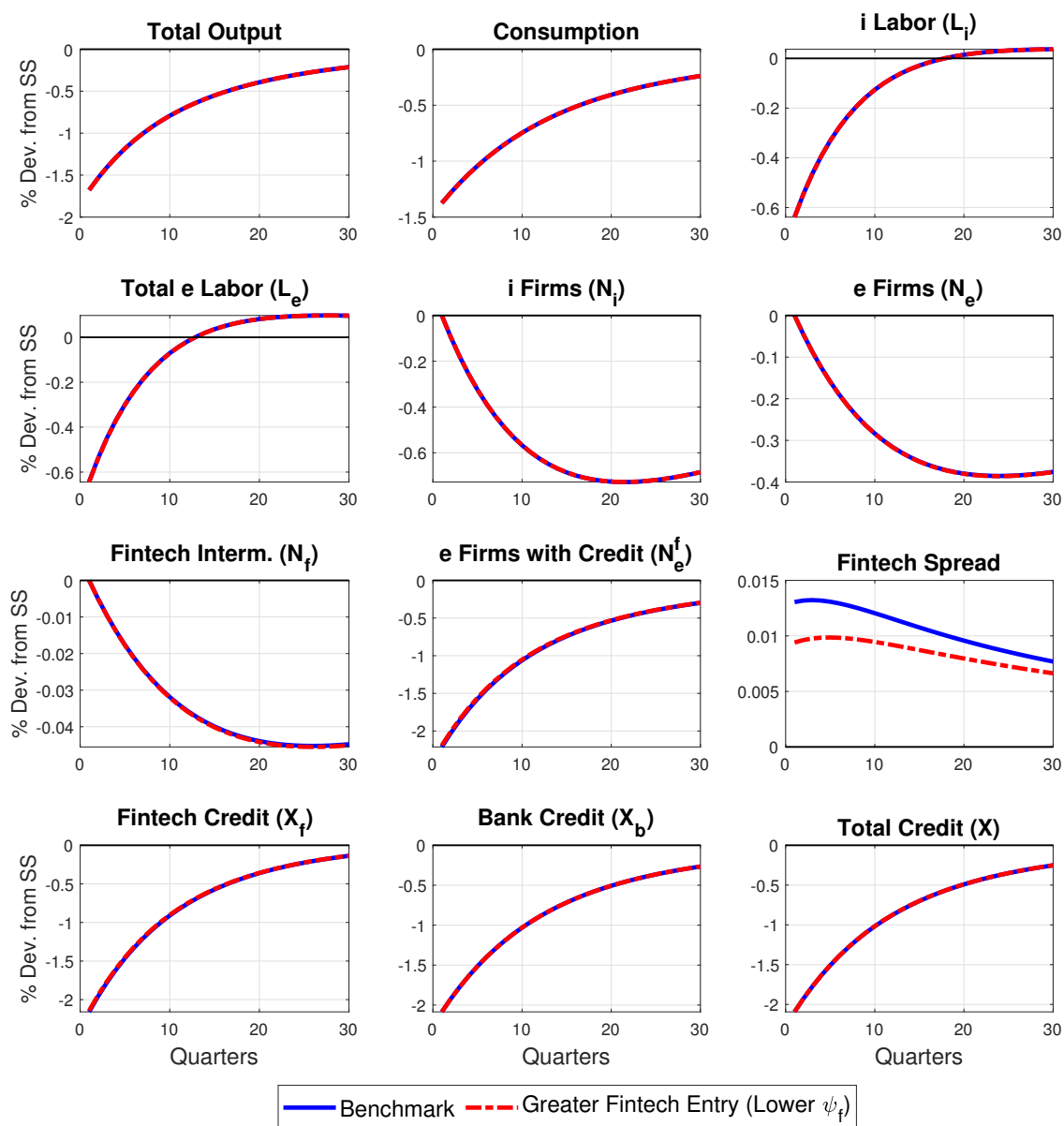
$$p_{e,t} = N_{e,t}^{\frac{1}{1-\varepsilon}} \rho_{e,t}, \quad (58)$$

$$D_{f,t} = N_{f,t}^{\frac{\varepsilon_f}{\varepsilon_f - 1}} d_{f,t}. \quad (59)$$

A.2 Additional Results and Robustness Checks

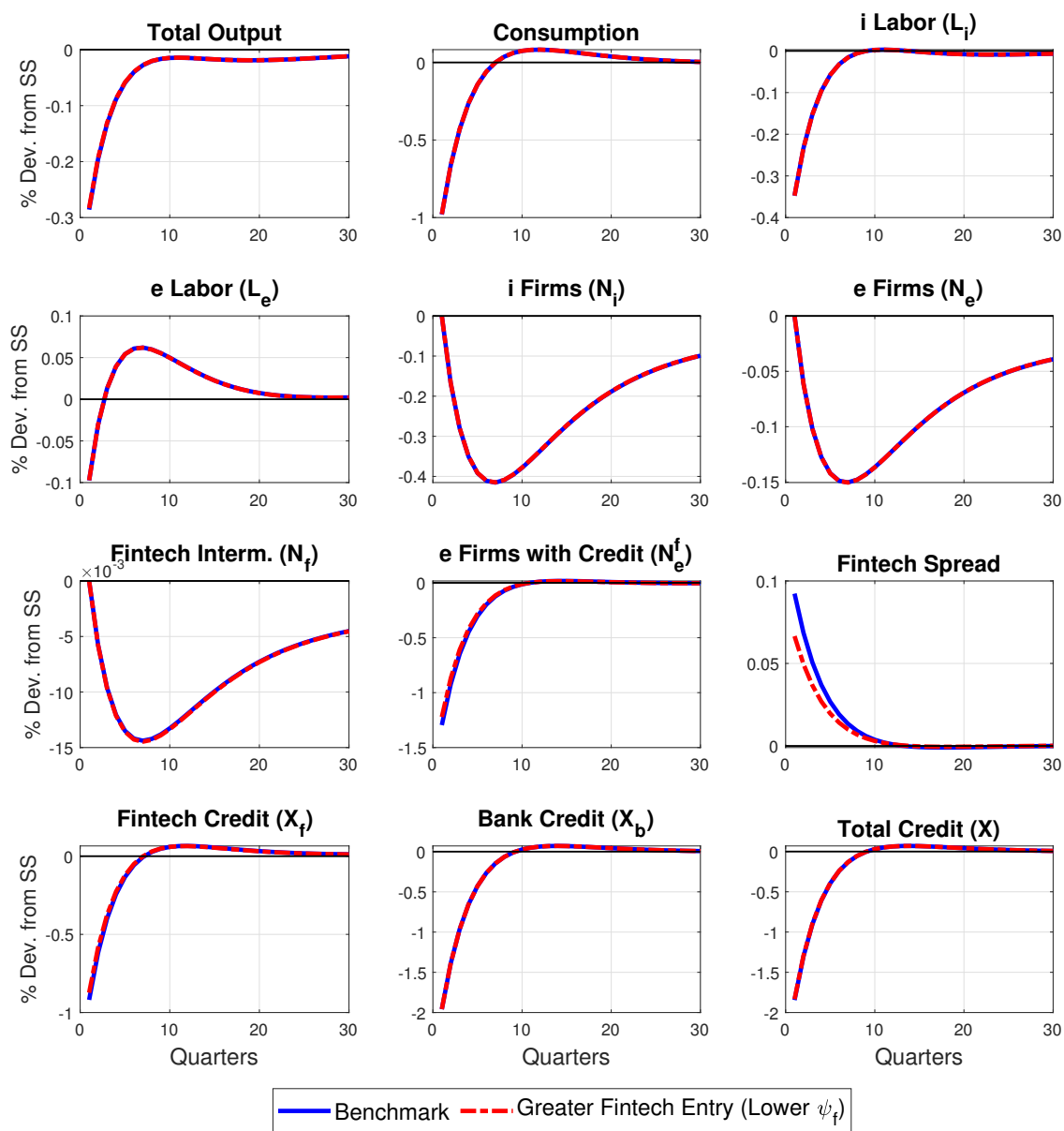
A.2.1 Benchmark Model Impulse Responses: Adverse Shock to Aggregate Productivity

Figure A1: Response to a Temporary Adverse Aggregate Productivity Shock



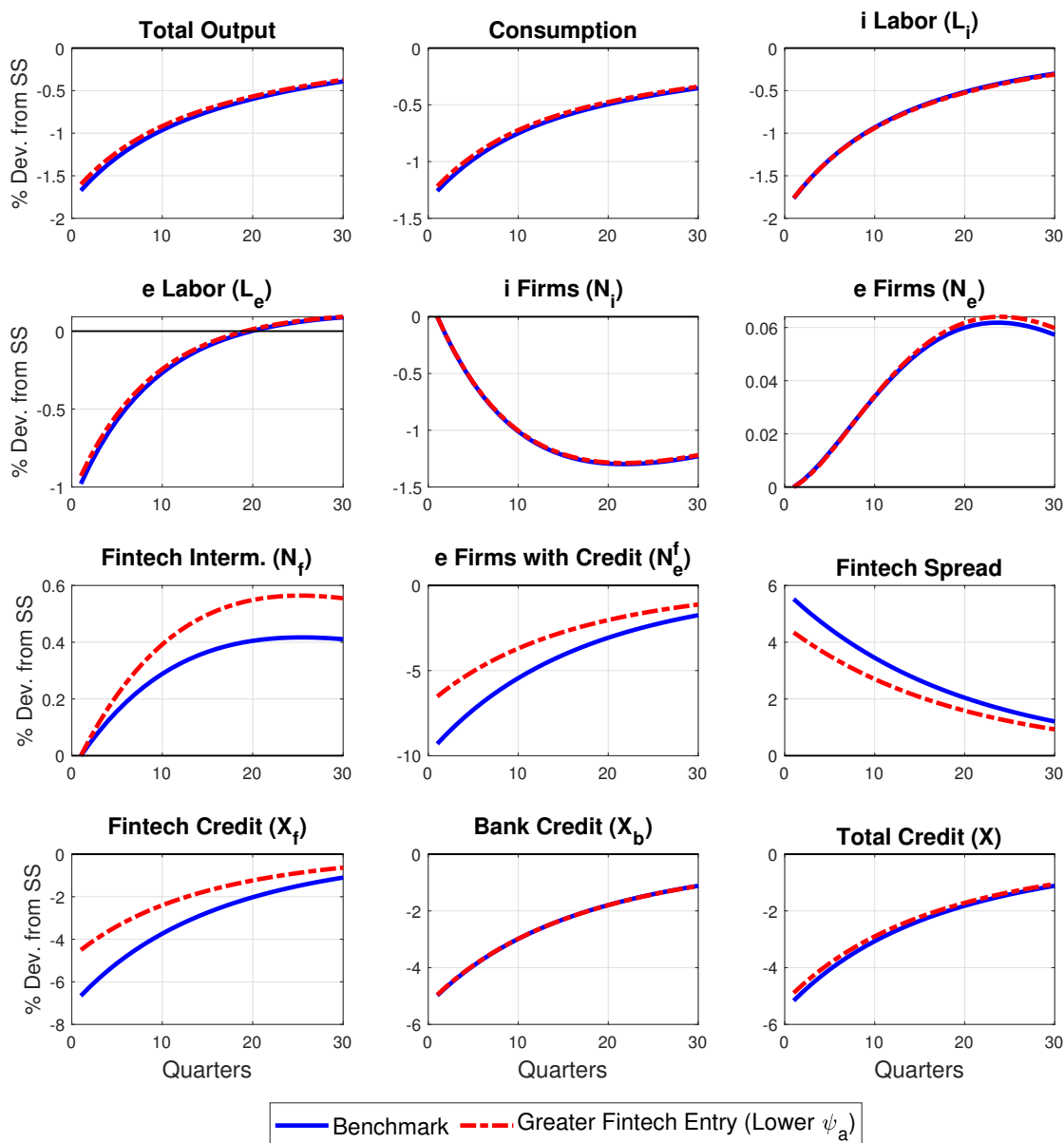
A.2.2 Benchmark Model Impulse Responses: Adverse Shock to Foreign Interest Rate

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 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 2000 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 Entry (Reduction in ψ_f or in ψ_a), Benchmark vs. Higher Baseline Share of Firms with Credit

Variable	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)
	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 $(N_i + N_e^f)/N$	0.001 PP	9.45 PP	-0.26 PP	4.92 PP
Ave. Fintech Lending Spread $(R_l^f - R_d^f)$	-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 Base-line Share of Firms with Credit

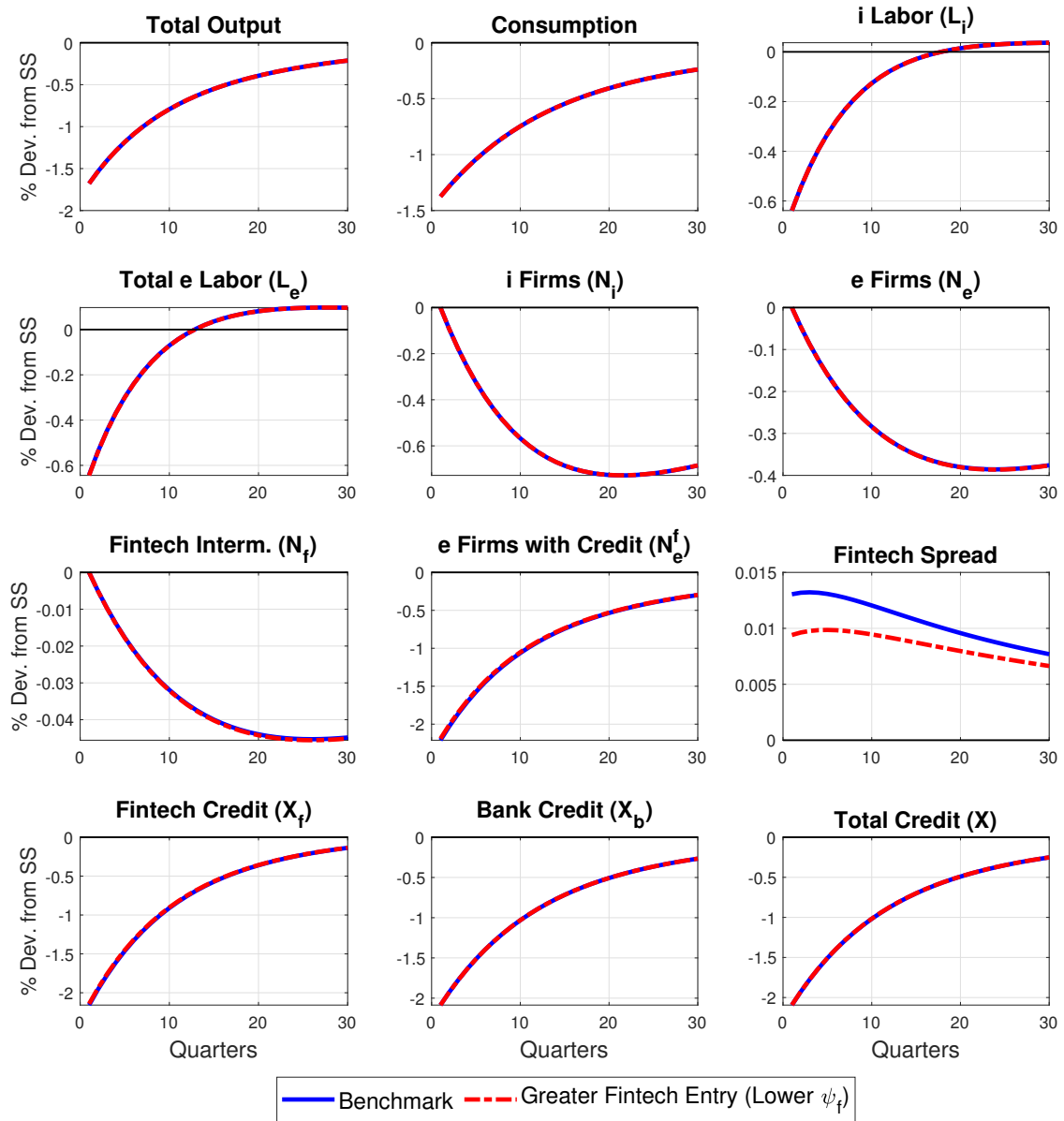
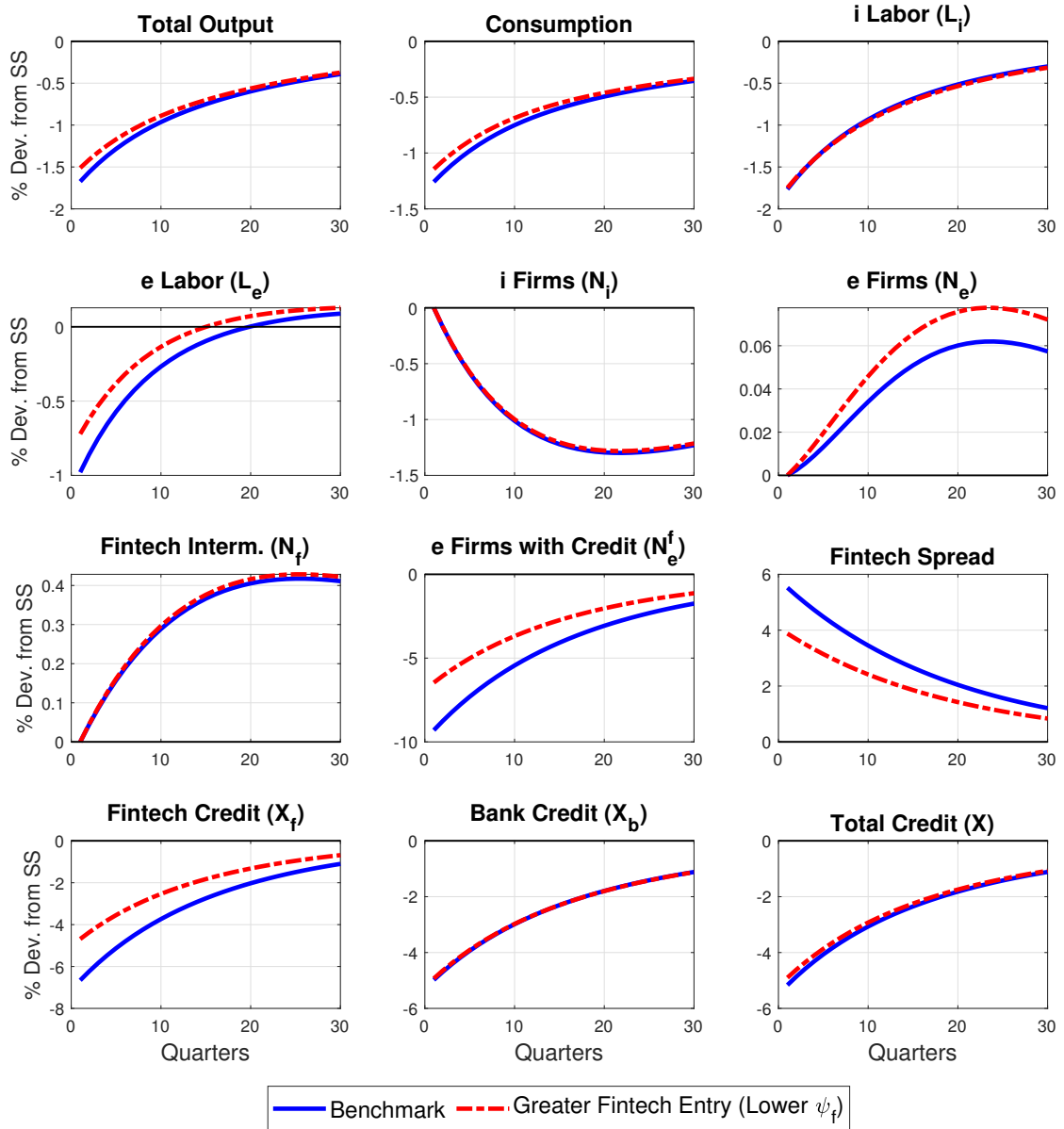


Figure A5: Response to a Temporary Adverse Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Higher Baseline Share of Firms with Credit



A.2.6 Model with Endogenous Traditional Bank Entry

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

Variable	Benchmark Model	Benchmark Model	Model with Endogenous	Model with Endogenous
	Calibration (lower ψ_f)	Calibration (lower ψ_a)	Traditional Bank Entry (lower ψ_f)	Traditional Bank Entry (lower ψ_a)
	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 $(N_i + N_e^f)/N$	0.001 PP	9.45 PP	0.013 PP	9.42 PP
Ave. Fintech Lending Spread $(R_l^f - R_d^f)$	-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 Intermediary 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	-7.91%	3.37	-3.28%	2.78	-19.93%
$\sigma_{c,t}/\sigma_{Y,t}$	0.98	3.66%	1.00	1.45%	1.06	8.34%
$\sigma_{inv,t}/\sigma_{Y,t}$	3.16*	4.81%	3.13	-1.10%	3.46	9.45%
$\sigma_{w_i,t}/\sigma_{Y,t}$	1.36	7.70%	1.41	3.52%	0.95	-30.18%
$\sigma_{w_e,t}/\sigma_{Y,t}$	0.99	-15.91%	0.96	-3.75%	1.18	19.51%
$\sigma_{L_i,t}/\sigma_{Y,t}$	0.82	7.35%	0.85	3.81%	0.55	-33.17%
$\sigma_{L_e,t}/\sigma_{Y,t}$	0.58	-18.24%	0.56	-4.47%	0.72	24.67%
$\sigma_{X_b,t}/\sigma_{Y,t}$	2.41*	7.60%	2.50	3.42%	1.85	-23.34%
$\sigma_{X_f,t}/\sigma_{Y,t}$	3.78	-27.55%	2.57	-32.00%	4.67	23.41%
$\sigma_{X_t,t}/\sigma_{Y,t}$	2.58	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 2000 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 Entry

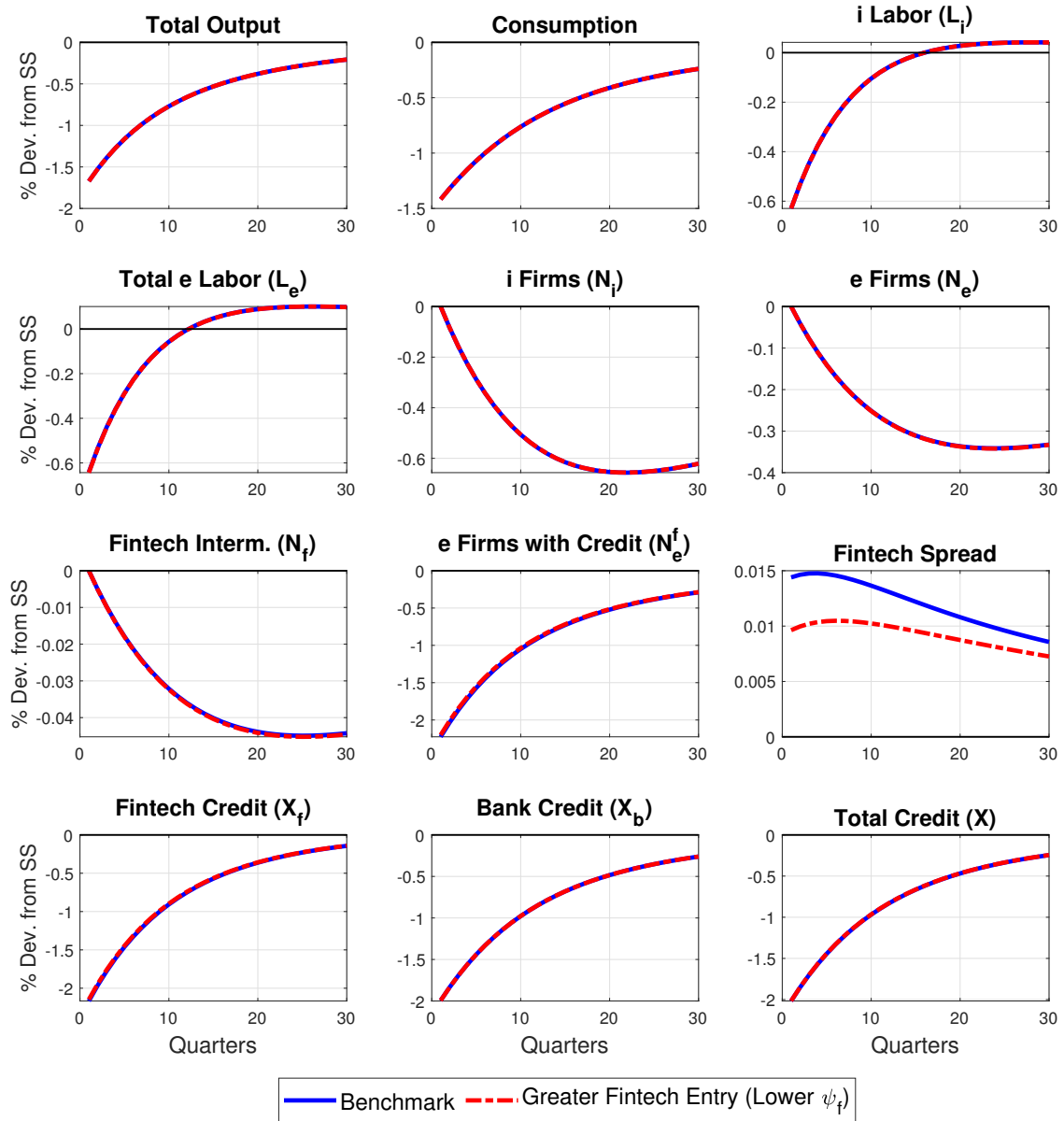
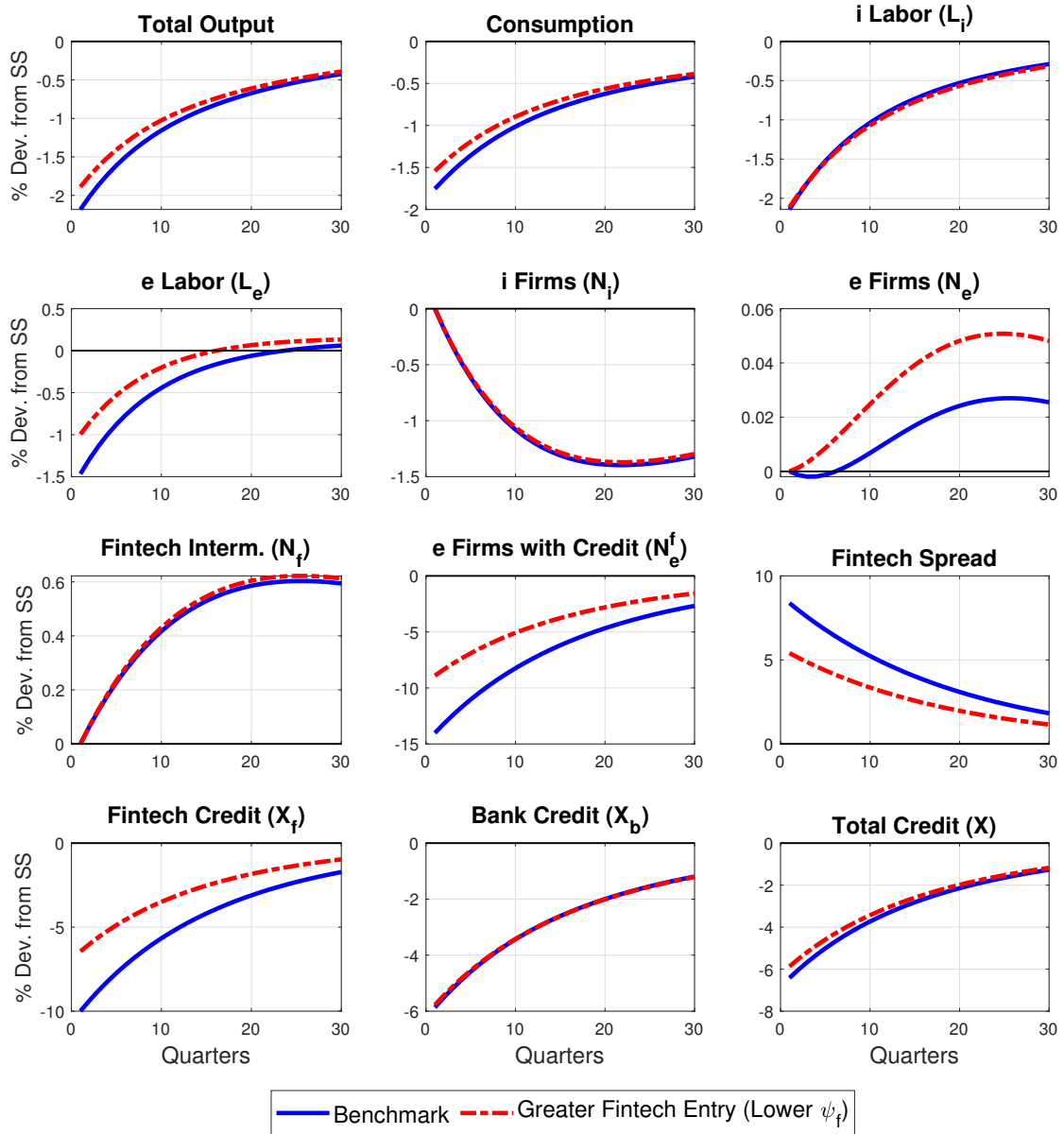


Figure A7: Response to a Temporary Adverse Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Model with Endogenous Bank and Fintech Entry



A.2.7 Model with Endogenous Traditional-Bank Entry

Table A5: Steady-State Changes in Response to Greater Fintech 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 $(N_i + N_e^f)/N$	0.001 PP	0.02 PP
Ave. Fintech Lending Spread $(R_l^f - R_d^f)$	-3.96 PP	-9.17 PP
Ave. Bank Lending Spread $(R_l^b - R_d^b)$	–	-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 2000 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 Entry, Oligopolistic Competition

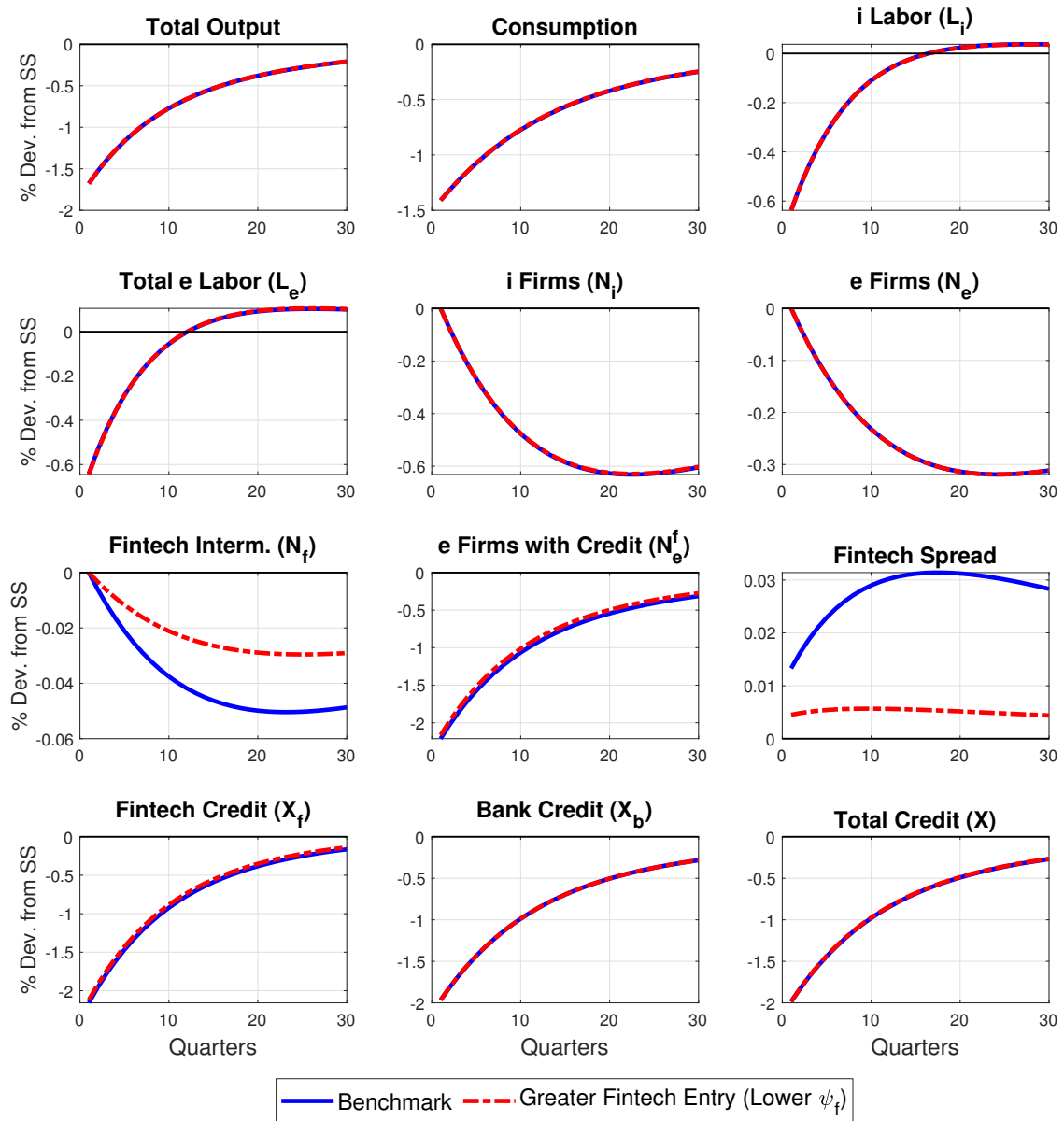
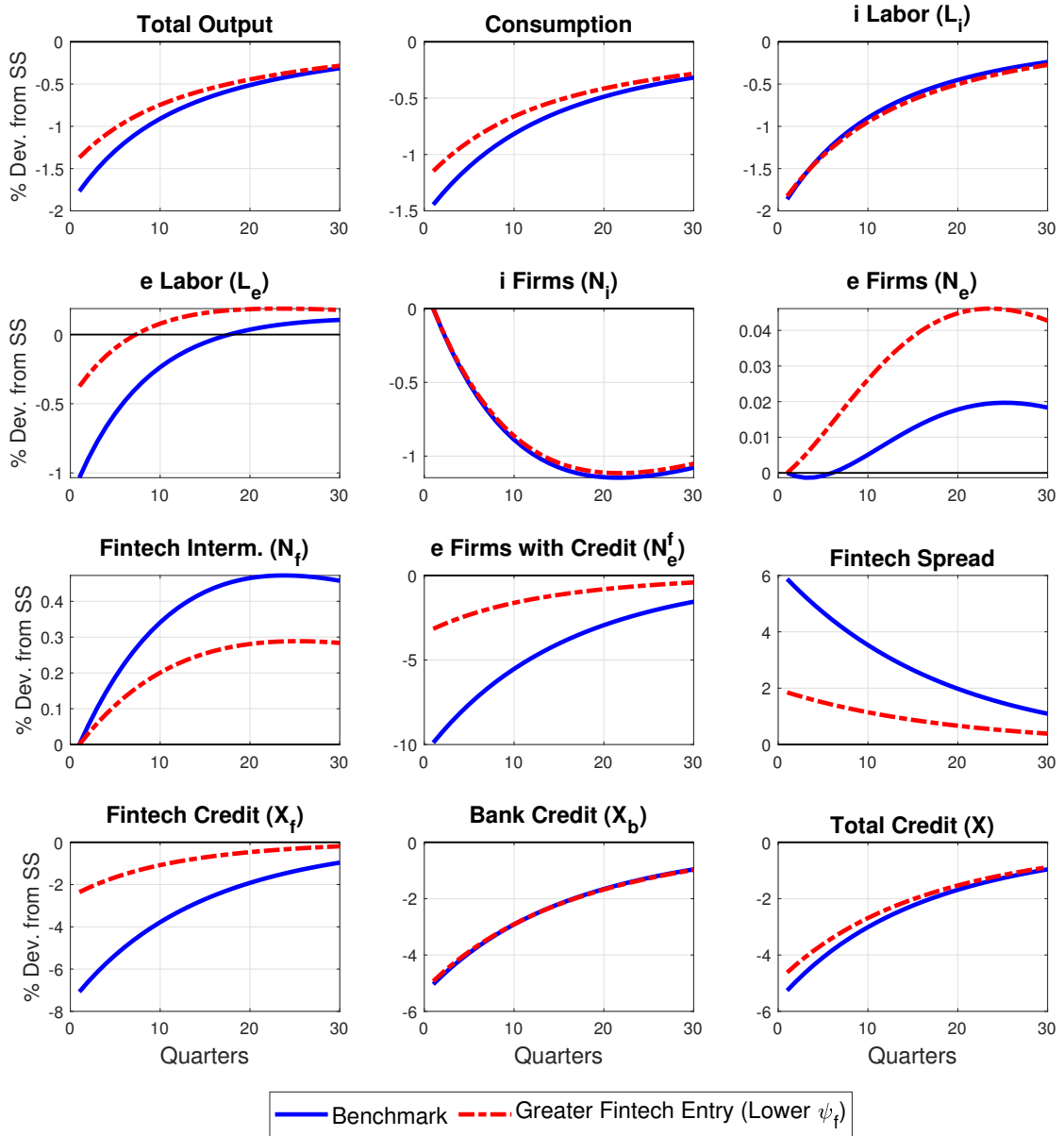


Figure A9: Response to a Temporary Adverse Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Model with Endogenous Bank and Fintech Entry, Oligopolistic Competition



A.2.8 Benchmark Model, Holding e -Firms' Idiosyncratic Productivities at their Baseline Values

Figure A10: Response to a Temporary Adverse Domestic Financial Shock (Exogenous Joint Reduction in $\varepsilon_{b,t}$ and $\varepsilon_{f,t}$), Holding Steady-State \tilde{a}_e^f and \tilde{a}_e^n at their Baseline Values

