



SINGAPORE

SELECTED ISSUES

July 2024

This paper on Singapore was prepared by a staff team of the International Monetary Fund as background documentation for the periodic consultation with the member country. It is based on the information available at the time it was completed on July 1, 2024.

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July 1, 2024

Approved By
**Asia and Pacific
Department**

Prepared by Kodjovi Eklou, Shujaat Khan, and Margaux MacDonald (APD).

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EXCHANGE RATE PASS-THROUGH TO INFLATION IN SINGAPORE¹

Singapore has addressed high inflation over the past years amid a tight labor market through several rounds of tightening of the exchange rate-based monetary policy. This paper estimates the exchange pass-through to inflation in Singapore with a particular focus on the role of labor market conditions. The paper first finds a strong exchange rate pass-through to inflation in Singapore, after accounting for the potential endogeneity of changes in the exchange rate. Further, it uncovers that labor market tightness dampens exchange rate pass-through and therefore could weaken monetary policy transmission. Overall, the results suggest that monetary policy should be more vigilant under a tight labor market condition. The paper then draws policy implications for taming inflation under tight labor market conditions.

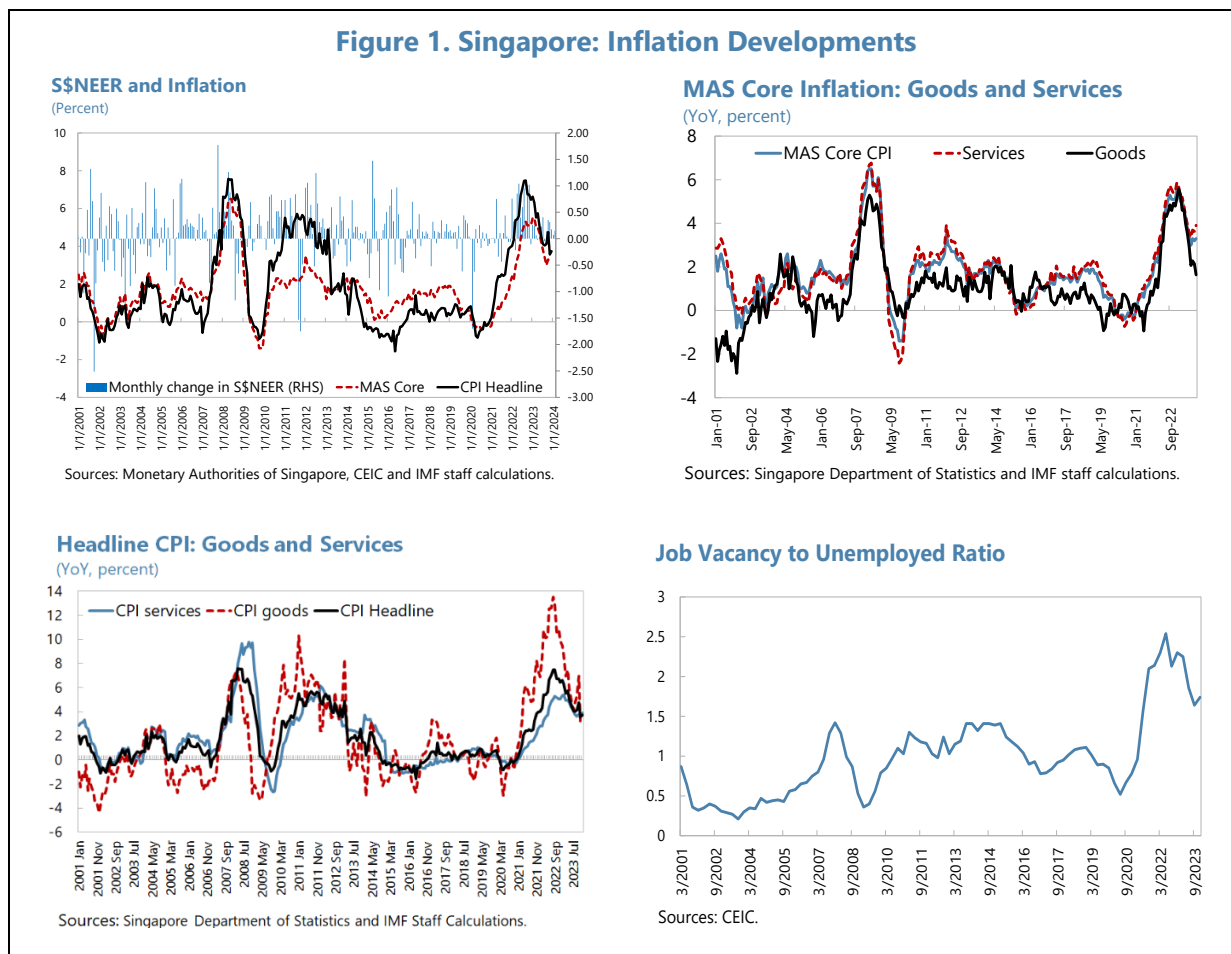
A. Background: Taking Stock of Recent Development in Inflation and Monetary Policy Tightening in Singapore

1. The Monetary Authority of Singapore (MAS) operates a basket, band, and crawl (BBC) exchange rate-based monetary policy framework in which the nominal effective exchange rate (S\$NEER) is managed against an undisclosed basket of currencies. The BBC can best be characterized by a forward-looking Taylor rule-like policy reaction function with the S\$NEER, instead of the interest rate, as the short-term policy instrument to minimize output gap and stabilize expected inflation (see Parrado, 2004; McCallum, 2006; and MAS, 2021). Given that Singapore is a small open economy, MAS sees the exchange rate as having a much stronger influence on inflation than the interest rate. The exchange rate is seen to affect prices through both the ‘imported inflation’ channel and the ‘derived demand’ channel. Under the ‘imported inflation’ channel, an appreciation of the Singapore dollar against currencies of major trading partners reduces the S\$ prices of imported goods and services, which subsequently dampens consumer prices. The ‘derived demand’ channel operates when changes in nominal exchange rate affect firms’ demand for domestic factors of production and hence the output gap. Under a positive output gap, an appreciation of the S\$ will reduce aggregate demand, leading firms to cut back on domestic production and hold back on investment and hiring, which narrows the positive output gap and dampens price pressures.

2. After surging amid the post-pandemic recovery, inflation has eased following multiple rounds of monetary policy tightening (Figure 1). Both headline and MAS core inflation increased rapidly in 2022, with the former peaking at 7.5 percent in September 2022 before moderating to 3.7 percent in December 2023. MAS core inflation fell to 3.3 percent in December 2023 from 5.5 percent in February 2023, while still showing some signs of persistence. Looking at the components of the CPI basket, both goods and services inflation have also begun to ease, with the latter showing more persistence. MAS responded to the rising inflationary pressures with five rounds of consecutive

¹ Prepared by Kodjovi Eklou.

tightening and has remained on pause since April 2023.² The labor market remains tight compared to its pre-pandemic level.



B. Estimating Exchange Rate Pass-Through in Singapore

3. A large literature investigates exchange rate pass-through to inflation including in Singapore. Recent cross-country works include Caselli and Roitman (2019), Carrière-Swallow et al. (2023), and Cheikh et al (2023), all putting an emphasis on state-dependent exchange rate pass-through. For instance, Cheikh et al. (2023) show that the exchange rate pass-through to consumer prices is high during periods of geopolitical tensions. Carrière-Swallow et al. (2023) find that while the exchange rate pass-through is low on average, it becomes large when uncertainty is high. The literature on exchange rate pass-through in the specific context of Singapore (see MAS, 2001; Ghosh and Rajan, 2009; and Tan et al., 2011) focused mostly on the exchange rate pass-through to import prices. Tan et al. (2011), the most recent work, find that there is a full-pass-through of exchange rate to import prices within 6 quarters and about 25 percent pass-through to CPI within the year.

² See IMF Country Report No. 2023/314 for more detail on the monetary policy tightening cycle.

4. We employ a two-stage empirical strategy consisting of identifying plausibly exogenous changes in exchange rates and estimating the pass-through of such identified exchange rate shocks to inflation. The exchange rate in Singapore is obviously endogenous given the exchange-rate based monetary policy. We follow an approach similar to Romer and Romer (2004) and Holm et al (2021) to identify plausibly exogenous monetary policy shocks. Our approach consists in using MAS monetary policy meetings level data and estimate the following equation.³

$$\Delta S\$NEER_m = \beta_0 + \beta_1 S\$NEER_{m-1} + \sum_{k=0}^1 \delta_k^\pi \pi_{m,t+k} + \sum_{k=0}^1 \delta_k^y y_{m,t+k} + \eta_m^{NEER} \quad (1)$$

Where $\Delta S\$NEER_m$ is the change in the logarithm of the $S\$NEER_m$ at meeting m , $S\$NEER_{m-1}$ is the logarithm of the $S\$NEER$ in the previous meeting. Meeting m takes place in year t , and control variables include inflation forecasts for the current year ($\pi_{m,t}$) and the next year ($\pi_{m,t+1}$), as well as growth forecasts for the current year ($y_{m,t}$) and the next year ($y_{m,t+1}$). Data on inflation and growth forecasts were taken from the consensus forecast for the corresponding month of each meeting. We take data on $S\$NEER$ as well as dates of monetary policy meetings from the [MAS website](#). Finally, η_m^{NEER} is a measure of exchange rate shock associated with meeting m obtained as a residual from equation (1). The intuition is that we obtain a measure of changes in $S\$NEER$ that is purged from the expectation regarding macroeconomic conditions, including inflation and output. η_m^{NEER} could also be seen as a measure of unexpected changes in $S\$NEER$.

5. We estimate plausibly exogenous exchange rate shocks by OLS using equation (1). Our estimates cover the period 2000m1 to 2023m10 and Table 1 shows results. The model explains about 30 percent of the variation in the change of $S\$NEER$ (similar to finding on monetary policy shocks estimates by Romer and Romer (2004), Holm et al. (2021), and Eklou (2023)). We find that, when MAS expects a strong growth in the current year and the next year, monetary policy is likely to be tightened while it is likely to do so when next year inflation is expected to be high. Figure 2 shows the estimated monetary policy shocks (η_m^{NEER}) from Table 1. As previously discussed, these monetary policy shocks capture unexpected or surprise changes in the $S\$NEER$. For instance, during the global financial crisis, MAS announced an upward recentering in April 2008 (after slight increase in the slope in October 2007), which translates into a surprise appreciation in $S\$NEER$ by about 1 percent in our measure. More recently, during the pandemic, in its March 2020 meeting, MAS set the slope at 0 percent and announced a downward re-centering at the prevailing level of the $S\$NEER$ which translated into an estimated surprise depreciation in the $S\$NEER$ by about 0.6 percent. The July 2022 off-cycle meeting, where MAS announced the upward recentering, translated into a surprise appreciation in the $S\$NEER$ by about 0.4 percent. Following Romer and Romer (2004)

³ Our specification is also similar to the reduced form estimate of MAS' implied policy reaction following a Taylor rule (MAS, 2021). [The monetary policy framework](#) of the MAS is arguably complex as not only the slope of the $S\$NEER$ can be changed but also, the width and the level at which the policy band is centered. MAS' monetary policy decisions are typically characterized by shifts in the slope of the $S\$NEER$ policy band and only occasionally by changes in the level of the mid-point (for instance if the growth/inflation outlook changes abruptly and rapidly such as at the time of the global financial crisis) or the width of the band (in face of a significant increase in the level of uncertainty, such as in 2001 and 2010). See Appendix VI of IMF Country report No. 22/233.

and Holm et al (2021), we obtain the monthly estimates of monetary policy shocks over January 2001 to October 2023, setting them to zero in months without a monetary policy meeting.

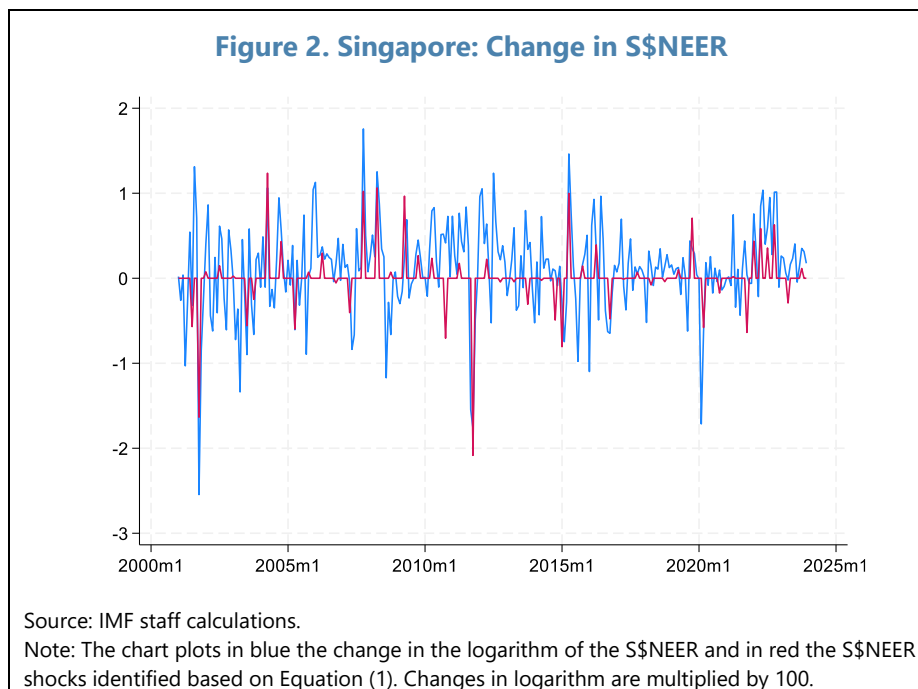


Table 1. Singapore: Determinants of the Changes in S\$NEER

$S\$NEER_{m-1}$	0.036** (0.016)
$y_{m,t}$	0.001* (0.000)
$y_{m,t+1}$	0.003** (0.001)
$\pi_{m,t}$	-0.002 (0.001)
$\pi_{m,t+1}$	0.001* (0.000)
β_0	-0.188** (0.078)
N	50
R-squared	0.296
Robust standard errors in parentheses.	

6. We estimate exchange rate pass-through to inflation in Singapore, accounting for the potential role of labor market conditions using the local projection framework over the period of 2000m1–2020m3.

Following the recent literature on state-dependent exchange rate pass-through to inflation (Caselli and Roitman, 2019; and Carrière-Swallow et al. 2023), we use the local projection approach. The local projection approach (Jordà, 2005) has interesting properties including being robust to misspecifications and flexible enough to accommodate state dependent analyses. More recently, Montiel Olea and Plagborg-Møller (2021) show that local projection inference is both simpler and more robust than standard autoregressive inference, whose validity is known to depend sensitively on the persistence of the data and on the length of the horizon. We estimate the following equation:

$$Y_{t+h} - Y_{t-1} = \alpha_0^h + \theta^h \eta_t^{NEER} + \lambda^h \eta_t^{NEER} \times vac_ratio_t + \sum_{j=0}^{12} \phi_j^h X_{t-j}^D + \sum_{j=0}^{12} \mu_j^h X_{t-j}^G + \xi_{t+h} \quad (2)$$

Where Y_t is the logarithm of the price index of interest (consumer price index, MAS core index, Goods CPI index and Services CPI index) and η_t^{NEER} is the S\$NEER shock (we also use the change in the logarithm of the S\$NEER in a baseline result).⁴ vac_ratio_t is the job vacancy ratio (the job vacancy to unemployed person ratio) taken from CEIC.⁵ The vector X_t^D contains domestic control variables and their 12 months lags. These controls include the output gap, lagged inflation, lagged \$NEER shocks, the job vacancy ratio and the lagged changes in log of the manufacturing producer price index. The output gap⁶ captures demand side pressures while the manufacturing producer price captures supply side price pressures. The vector X_t^G includes global factors⁷, including the global output gap, the global supply chain pressures index, and the changes in the logarithm of global food price and oil price indices.

7. We present cumulative impulse responses functions (IRFs) as deviation in percent of initial value. In equation (2), θ^h captures the percent response of prices to a 1 percentage point appreciation (increase) in the S\$NEER shock at a horizon of h months, without accounting for the potential role of job vacancy or labor market tightness. We then compute the cumulative impact of the 1 percent S\$NEER appreciation shock accounting for the role of labor market tightness as $\theta^h + \lambda^h \times p75_{vac}$, where $p75_{vac}$ represents the 75th percentile value of the job vacancy ratio series.

⁴ MAS core inflation excludes volatile components such as private road transportation and accommodation. We use data on the goods and services categories of the CPI basket and corresponding weight to calculate the corresponding CPI indices. See further details in the Data Appendix.

⁵ This data is not available at the monthly frequency and therefore we use the quarterly data.

⁶ Following Binici et al (forthcoming), we obtain monthly output gap series by applying the HP filter to the monthly industrial production index. The global output gap is obtained similarly, using data on global industrial production from Baumeister and Hamilton (2019).

⁷ The global supply chain pressure index is taken from [the New York Fed website](#). The index is built by Benigno et al. (2022) and captures supply chain disruptions according to the Baltic Dry Index (BDI), the Harpex index, air freight costs, and some components of the Purchasing Managers' Index (PMI), such as delivery time, backlogs, and purchased stocks. Global food and oil price indices are taken from the [IMF website](#).

8. Our results show that the exchange rate pass-through, in absolute terms, could be under-estimated without taking into account potential endogeneities issues. Figure 3 shows the estimates of the pass-through using changes in the logarithm of the S\$NEER, while Figure 4 employs the monetary policy-induced exchange rate shocks (η_m^{NEER}) identified in equation (1). Overall, results show lower pass-through in Figure 3 compared to Figure 4. For instance, considering headline inflation, the average exchange rate pass-through is about twice as large when using the plausibly exogenous exchange rate shocks. Further, when we account for the tightness of the labor market, we fail to identify a pass-through without accounting for the endogeneity of the exchange rate policy. This pattern is similar when looking at the components of the CPI basket (see Figure 5 and Figure 6). Overall, our findings suggest that without taking into account endogeneity issues, the exchange rate pass-through is likely to be perceived as weaker than warranted. This could be due to the fact that exchange rate appreciations are more likely to take place when upward inflationary pressures are expected. The identification strategy that we used in equation (1) allows to mitigate this issue by isolating changes in the S\$NEER that are not driven by expectations on the macroeconomic conditions.

9. We find that the S\$NEER pass-through to inflation is strong (Figure 4). The results show that the exchange rate pass-through to headline inflation could be relatively quick and strong, with a 1 percent appreciation shock leading to a cumulative 2 percentage points reduction in about 9 months. More specifically, the magnitude of the pass-through implies for instance that for an initial inflation rate of 3 percent, a 1 percent appreciation shock in the S\$NEER would lead to an inflation rate of about 1 percent in 9 months. Regarding MAS core inflation, a 1 percent appreciation shock would lead to about 1 percentage point cumulative reduction over 9 months. To compare, recent estimates for advanced economies show a pass-through coefficient about 0.1 percentage point cumulatively over 12 months (see Carrière-Swallow et al., 2021).

10. The pass-through could be however significantly weakened under a tight labor market condition (Figure 4). Labor market tightness severely impacts the transmission of the S\$NEER appreciation shocks to inflation, with a marginal impact representing only about fourth and half of the impact previously discussed for headline and MAS core inflation, respectively. The weaker pass-through from exchange rate to inflation during periods of labor market tightness could be due to the fact that labor market typically tightens more in response to domestic shocks, in which case, the exchange rate pass-through is usually subjected to a substantial time lag. While this concern should be mitigated by the inclusion of the output gap among the controls to account for demand side pressures on inflation, other relevant demand side factors not accounted for could play a role. While the marginal impact estimated for Singapore under a tight labor market conditions is low compared to normal conditions, it remains large compared to estimates found in advanced economies on average.

11. The pass-through is larger for goods than for services (Figure 6). Our results show that the strong pass-through is mainly driven by the goods components of the CPI basket, which tend to respond more quickly and strongly than the services components. More specifically, goods CPI responds to a S\$NEER shock (in statistically significant manner) two months ahead of services CPI. Regarding headline CPI, while a 1 percent appreciation is likely to reduce goods inflation by 2 percent cumulatively in 7 months, it reduces services inflation by about 1 percent. Finally, while both

the pass-through to goods and services CPI is weaker under a tight labor market condition, it is more so for services inflation. Indeed, while the pass-through is about halved for goods CPI, under a tight labor market condition, it represents about fourth of the average effect for services inflation. Overall, this result suggests that exchange rate pass-through to services CPI is likely to be severely weakened under tight labor market conditions.

12. We undertake various robustness checks (Appendix II). These include additional controls (certificate of entitlement quotas, GST hikes), redefining the good and services baskets and employing an alternative measure of job vacancy. First, certificates of entitlement (COE) quotas have a significant impact on the private transport component of headline inflation. We address this by running a robustness check including the changes in the logarithm of COE quotas among domestic controls. Next, goods and services taxes (GST) have a significant influence on inflation and have been historically hiked during periods of tight labor market.⁸ To account for a potential omitted variable bias regarding the exclusion of GST, we control for whether in a given year there was a GST rate hike.⁹ Third, we redefined the goods CPI basket to include “Utilities and other fuels” and estimate the impulse response function. Finally, given that the labor market tightness is a key aspect of our analysis, we employ a different measure. In our baseline, we used the job vacancy to unemployed persons ratio. Although this is a widely accepted measure of labor market slack, one shortcoming in the context of Singapore is that while the numerator accounts for the total workforce, the denominator covers only unemployed residents. We resort therefore to the job vacancy rate, a broader measure, defined as the total number of job vacancies divided by the total demand for manpower.¹⁰

13. Our results are broadly robust to accounting for potential omitted variables, employing a different measure of labor market tightness and considering a longer horizon for impulse responses (Figure 7-13). We find that, accounting for COEs quotas (Figure 7), controlling for episodes of GST hikes (Figure 8 and 9), redefining the CPI basket by including “Utilities and other fuels” in goods category (Figure 10) and using a broader measure of labor market tightness (Figure 11 and 12) do not materially change our main results. For instance, while the results show a more significant impact of labor market tightness on exchange rate pass-through with the job vacancy rate, they remain in line with our finding of a relatively subdued pass-through under a tight labor market condition.

14. Finally, we also undertake a robustness check considering a 24-months horizon. Our results in Figure 13 show that the transmission of the exchange rate shocks persist mainly only over

⁸ We take data on COE quotas from [Singstat](#) and information on GST hikes from the [Inland Revenue Authority of Singapore](#).

⁹ More specifically, we include a dummy variable taking the value 1 in years where a GST hike took place over the period.

¹⁰ The data on the job vacancy rate is taken from the Ministry of Manpower.

about 14 months (except for goods CPI where the impact can persist up to 20 months).¹¹ The extension of the horizon beyond the standard 12-months used in the related literature (e.g., Carrière-Swallow et al., 2023)) could be an area for future research, given that the quality of statistical inference within the local projection framework could be weakened at higher projection horizons.

C. Conclusion and Policy Implications

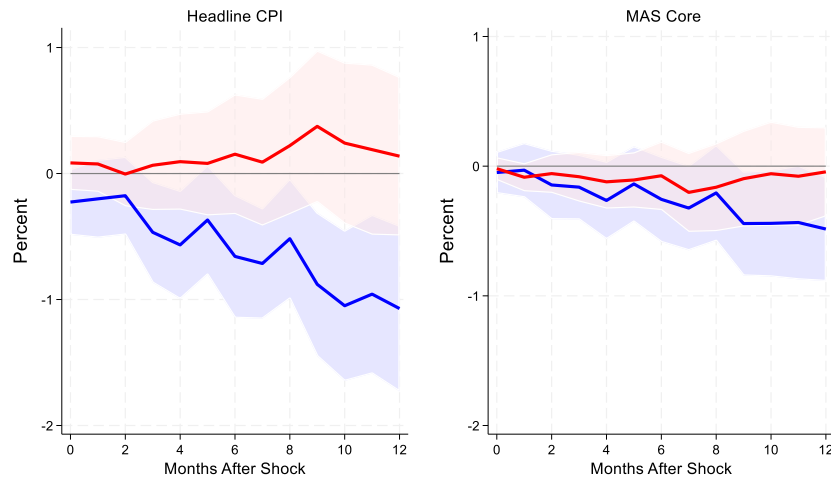
15. Our findings suggest that the exchange rate pass-through to inflation is strong in Singapore but could be weakened under tight labor market conditions, especially for services inflation. Once endogeneity issues are plausibly addressed, the exchange rate pass-through is estimated to be strong, especially for the good components of the CPI basket. However, under tight market conditions, the pass-through is found to be severely weakened and more so for the service components of the CPI basket. Overall, our findings suggest that the exchange rate-based monetary policy serves Singapore well, but it would need to be more vigilant when the labor market is tight.

16. Further, policies designed to ease structural labor market tightness could help support monetary policy to ensure price stability in Singapore. This is consistent with a recent study on the US that suggests that dealing with the inflationary pressures originating from a tight labor market would require policy actions that bring labor demand and supply into a better balance (Bernanke and Blanchard, 2023). Indeed, recent analysis by MAS suggests an important role for persistent matching frictions in the labor market, potentially due to a shortage of technology skills in the short-term and a recent shift in the foreign workforce leading to skill shortages in sectors such as health and social services.¹² More specifically, enhancing existing policies such as [Career Conversion Programs](#) to equip workers with skills could help ease matching frictions.

¹¹ Note that the quality of statistical inference within the local projection framework could be weakened at higher projection horizons.

¹² See the [Macroeconomic Review, Volume XXII, Issue 1, April 2023](#).

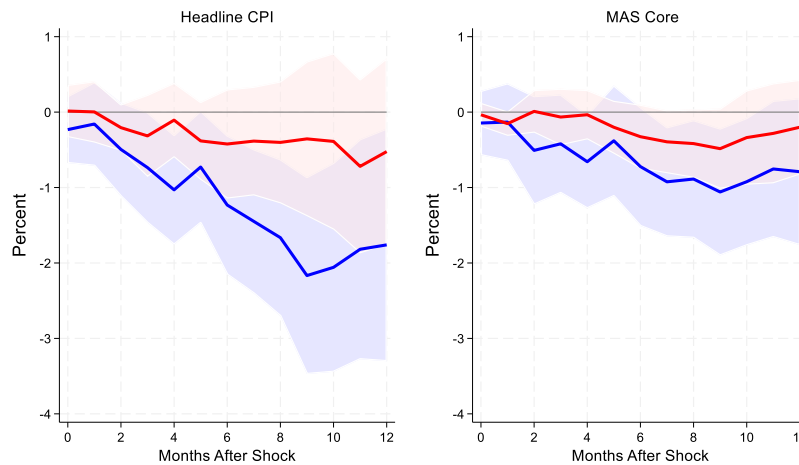
Figure 3. Singapore: Exchange Rate Pass-Through to Headline and MAS Core Inflation—Baseline



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation. The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

Figure 4. Singapore: Exchange Rate Pass-Through to Headline and MAS Core Inflation – Exogenous Changes in S\$NEER



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

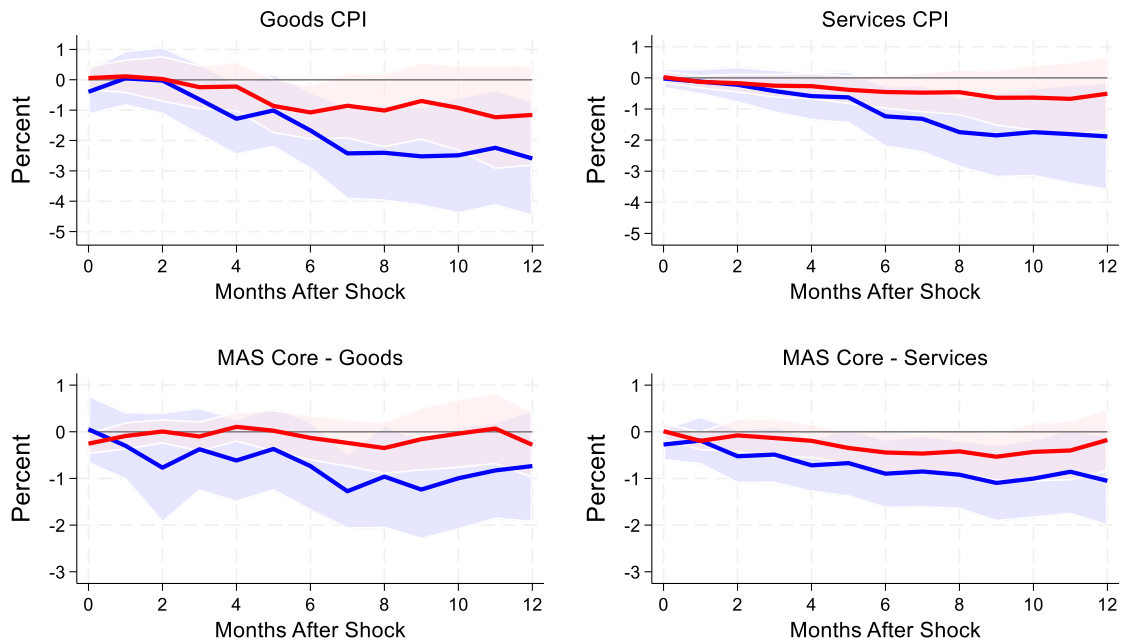
Figure 5. Singapore: Exchange Rate Pass-Through to Goods and Services Inflation – Baseline



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation. The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). The MAS core goods exclude private transportation category while MAS core services exclude the accommodation (housing) category. 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

Figure 6. Singapore: Exchange Rate Pass-Through to Goods and Services Inflation – Exogenous Changes in S\$NEER



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). The MAS core goods exclude private transportation category while MAS core services exclude the accommodation (housing) category. 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

Appendix I. Data Appendix

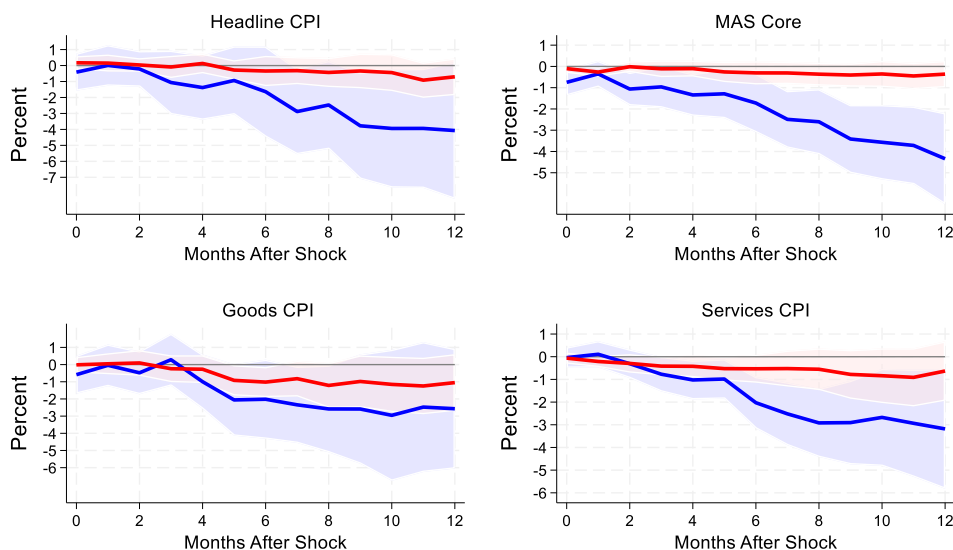
This Appendix describes the components of the CPI baskets included in goods and services.

Table 1. Singapore: MAS CPI -All Items - Goods and Services Components	
Services	Goods
Food Serving Services	Food Excl Food Serving Services
Housing & Utilities	Clothing & Footwear
Household Services & Supplies	Household Durables
Outpatient Services	Medicines & Health Products
Hospital Services	Private Transport
Health Insurance	Telecommunication Equipment
Public Transport	Recreational & Cultural Goods
Other Transport Services	Newspapers, Books & Stationery
Postage & Courier Services	Textbooks & Study Guides
Telecommunication Services	Alcoholic Drinks & Tobacco
Recreational & Cultural Services	Personal Effects
Holiday Expenses	
Tuition & Other Fees	
Personal Care	
Social Services	
Other Miscellaneous Services	

Table 2. Singapore: MAS Core – Goods and Services Components	
Services	Goods
Food Servicing Services	Food excluding services
Utilities and other fuels	Clothing & Footwear
Household Services & Supplies	Household Durables
Healthcare: Outpatient Services	Medicines & Health Products
Healthcare: Hospital Services	Telecommunication Equipment
Public Road Transport	Recreational & Cultural Goods
Other Travel & Transport	Newspapers, Books & Stationery
Postage & Courier Services	Textbooks & Study Guides
Telecommunication Services	Alcoholic Drinks & Tobacco
Recreational & Cultural Services	Personal Effects
Holiday Expenses	
Tuition & Other Fees	
Personal Care	
Notes: Some items were excluded as full series starting from 2000 were unavailable; adjustments were made. MAS Core goods exclude non-durable household goods. MAS Core services exclude domestic & household services, healthcare insurance, social services, other miscellaneous services. Non-durable household goods and domestic & household services were replaced by the broader category of household services & supplies, included in MAS Core services.	

Appendix II. Robustness Tests

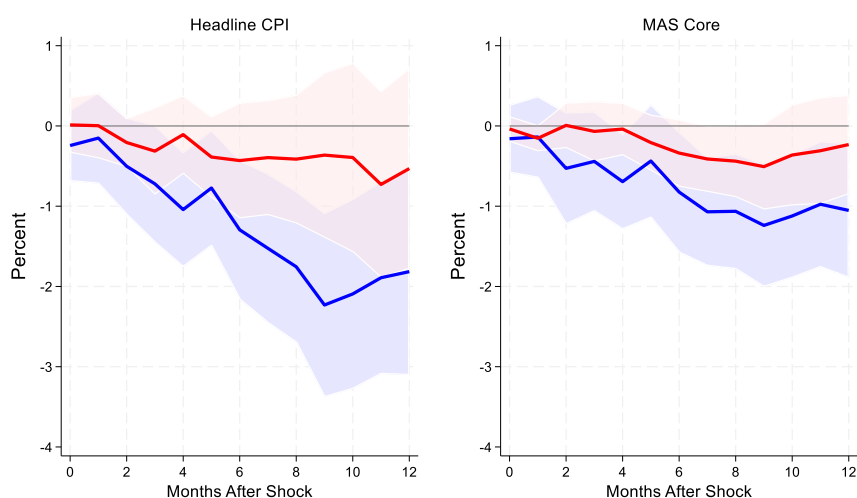
Figure 1. Singapore: Exchange Rate Pass-Through to Inflation – Controlling for Certificate of Entitlement (COEs)



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

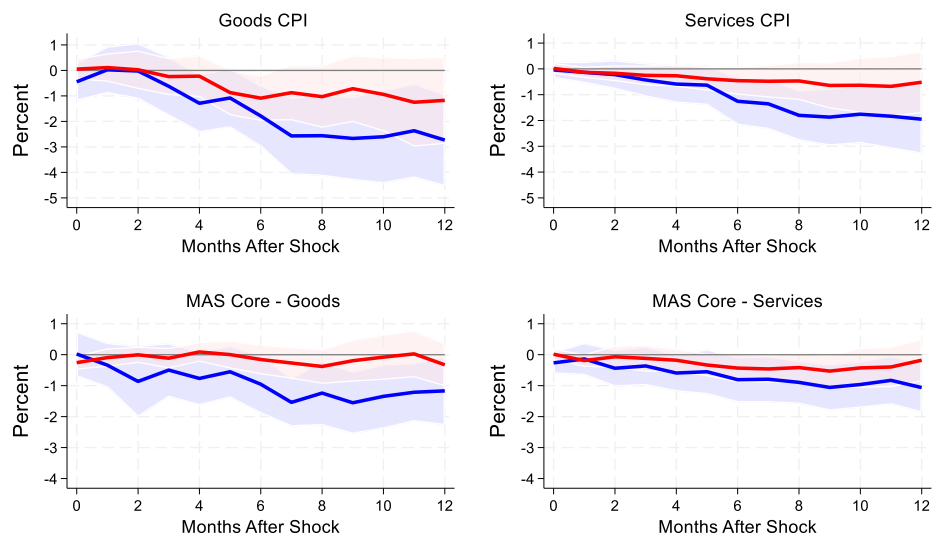
Figure 2. Singapore: Exchange Rate Pass-Through to Inflation – Controlling for GST Hikes



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). We include among domestic controls indicators of GST hikes across the sample period. The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

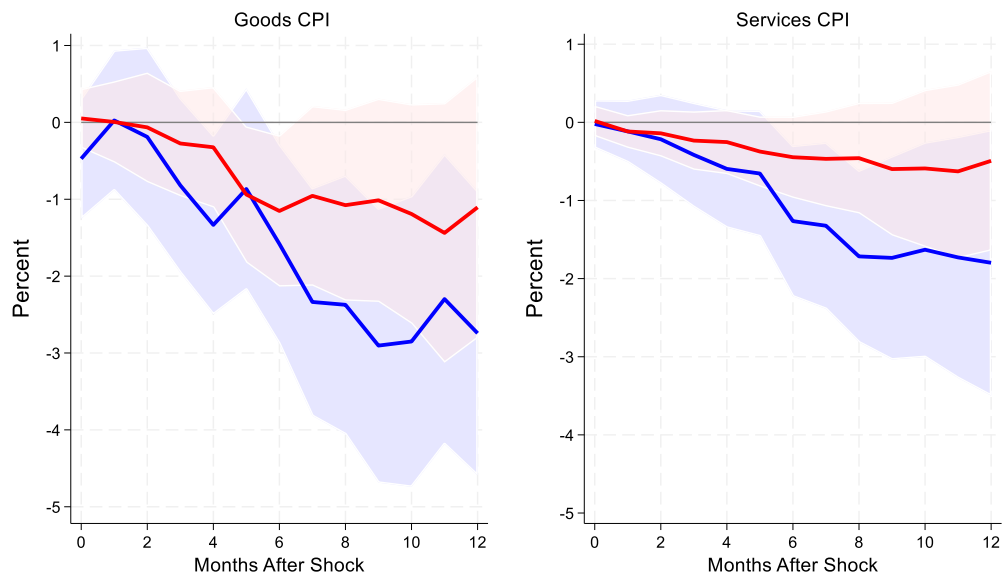
Figure 3. Singapore: Exchange Rate Pass-Through to Goods and Services Inflation – Controlling for GST hikes



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). We include among domestic controls indicators of GST hikes across the sample period. The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

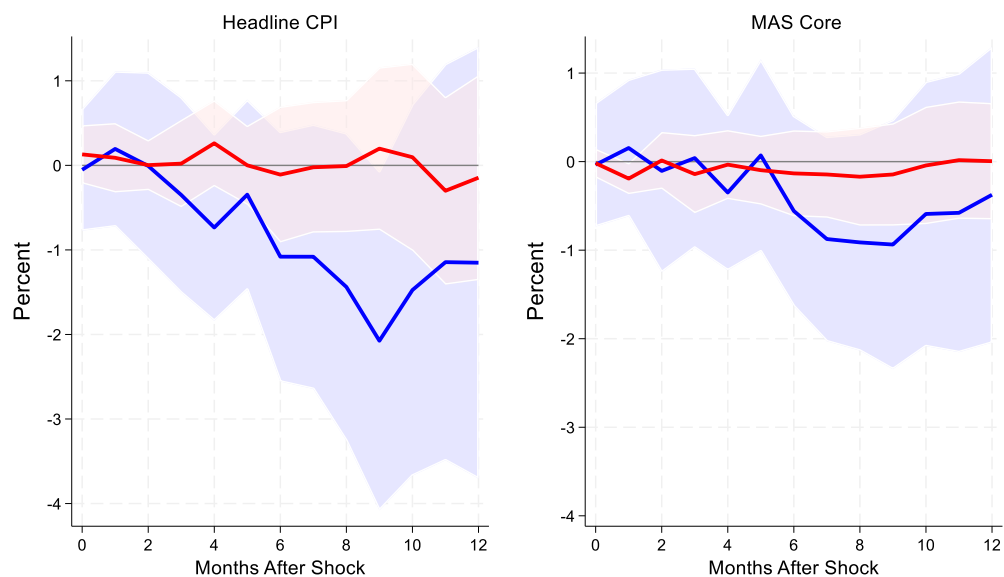
Figure 4. Singapore: Exchange Rate Pass-Through to Good and Services Inflation – Redefining Good and Services Baskets



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). We include the "utilities and other fuels" category in goods basket and exclude it from services compared to the baseline estimates. The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). The MAS core goods exclude private transportation category while MAS core services exclude the accommodation (housing) category. 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

Figure 5. Singapore: Exchange Rate Pass-Through to Inflation – Using Job Vacancy Rate



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). Job Vacancy Rate for a quarter is defined as the total number of job vacancies divided by the total demand for manpower at the end of the quarter. The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

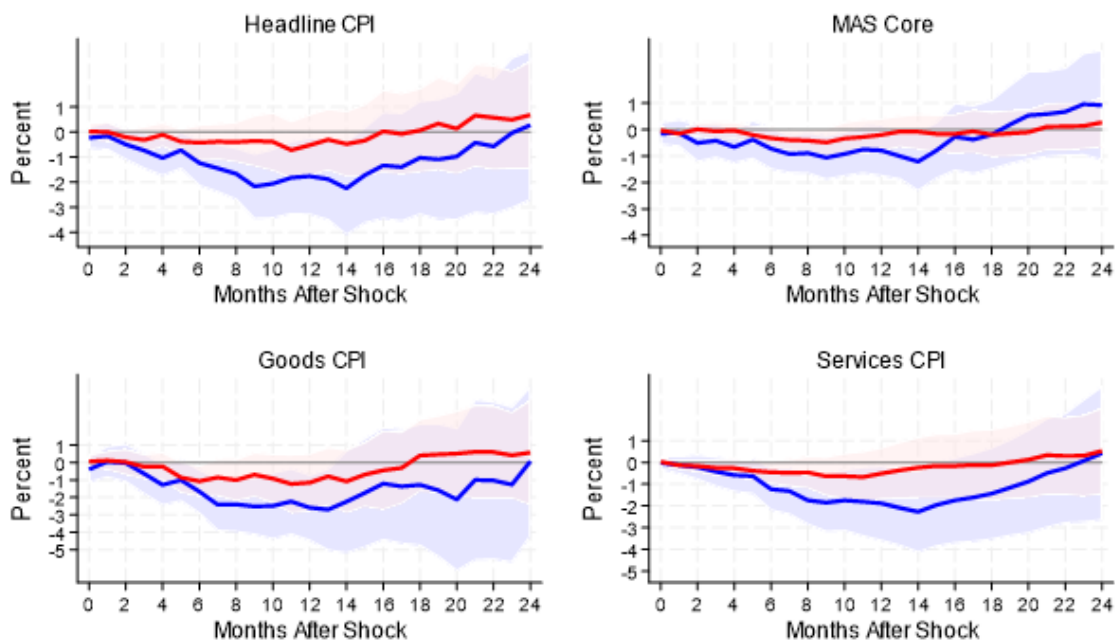
Figure 6. Singapore: Exchange Rate Pass-Through to Goods and Services Inflation – Using Job Vacancy Rate



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). Job Vacancy Rate for a quarter is defined as the total number of job vacancies divided by the total demand for manpower at the end of the quarter. The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

Figure 7. Singapore: Exchange Rate Pass-Through Inflation – Results Over a 24-Months Horizon



Source: IMF staff calculations.

Notes: This figure shows the cumulative response of inflation to 1 percent appreciation in the S\$NEER, on the percentage change in inflation, using the plausibly exogenous shocks (η_t^{NEER}). The blue line shows average impact (θ^h), while the red line the impact of the appreciation, conditional on the 75th percentile of job vacancy ratio in the sample ($\theta^h + \lambda^h \times p75_{vac}$). 90 percent confidence interval in shaded areas is based on Newey-West standard errors (robust to autocorrelation).

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SPILOVERS FROM CHINA'S GROWTH SLOWDOWN TO THE SINGAPORE ECONOMY ¹

China's economy is facing significant headwinds, including an ageing population and slowing productivity growth. As a result, growth is projected to moderate in the medium term. This moderation is expected to weigh on growth in ASEAN trading partner countries over the medium term due to the complexity of production processes via global value chains, in which China is a key player and ASEAN countries are increasingly linked. We examine the impact of this transition on Singapore from three perspectives. First, using global input-output tables we show that there are select sectors in Singapore that are important contributors to domestic value added but are particularly exposed to a slowdown in China. We then use empirical methods and estimate that a 1 percentage point decline in Chinese domestic growth is expected to reduce trend growth in ASEAN countries cumulatively by about 1 percentage point over the medium term (five years), mainly through a decline in the growth of capital stock—suggesting important impacts on investment in ASEAN countries from a slowdown in China. Finally, a general equilibrium model suggests that growth spillovers from China to ASEAN are significant and the spillovers are further amplified by the region's deep integration in global value chains.

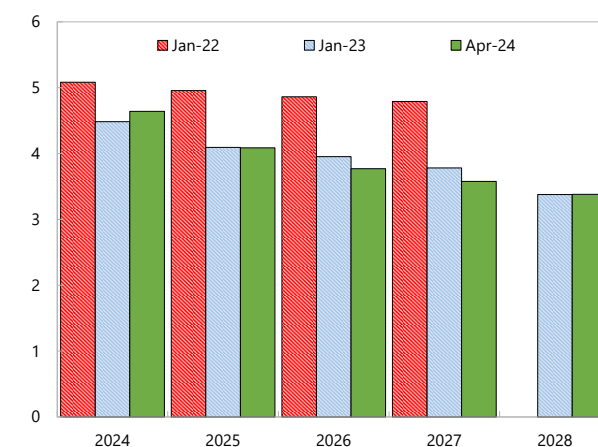
A. China's Growing Influence in Asia

1. GDP growth is expected to slow in China over the medium term amid longstanding headwinds. As its population ages and productivity growth remains low, growth in China is expected to slow to just over 3 percent in the medium term. In recent years, IMF staff have revised growth projections to suggest that this transition will happen earlier than previously expected (Figure 1). This moderation in GDP growth is projected to be broad-based, with consumption and investment growth slowing.

2. The decline in trend growth in China will likely impact other countries in the Asia-Pacific region, including Singapore. As documented in the IMF's

October 2023 Regional Economic Outlook for Asia and the Pacific, China's importance in the global economy has increased significantly over the past three decades and it has been a crucial driver of trade integration in Asia. Much of this can be attributed to China's insertion in global value chains

Figure 1. Singapore: IMF China Growth Projection
(percent)

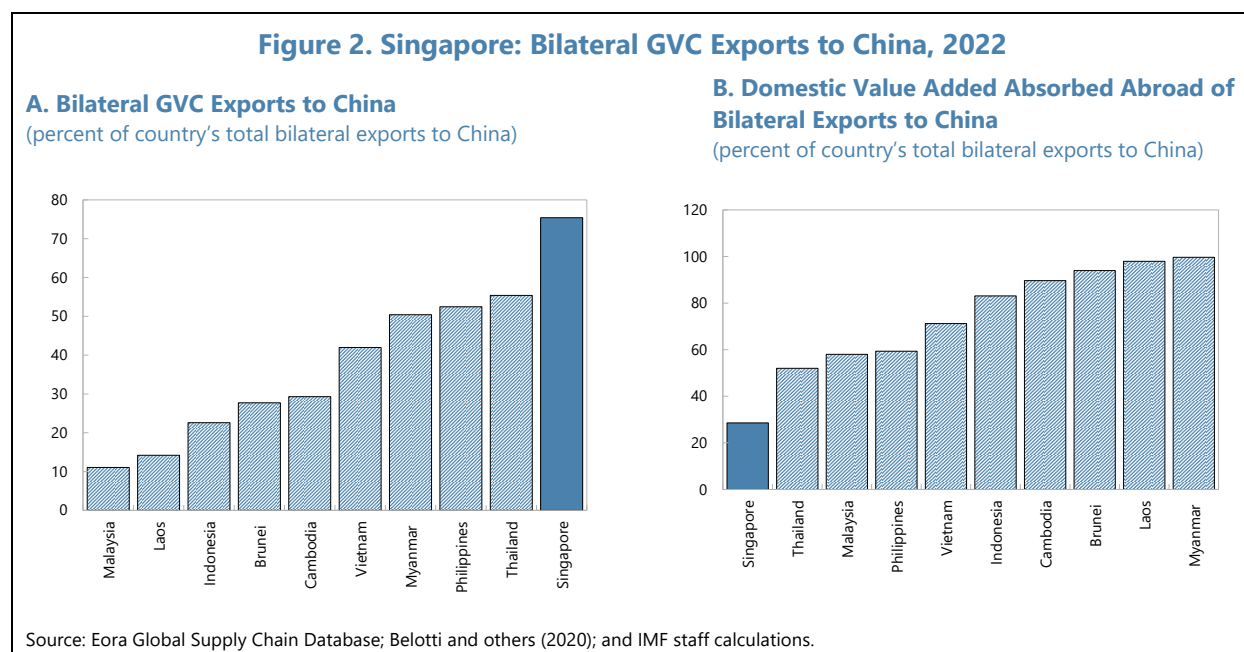


Source: IMF World Economic Outlook.

Note: Legend dates indicate WEO vintage.

¹ Prepared by Kodjovi Eklou, Shujaat Khan, and Margaux MacDonald.

(GVCs), which are defined as such when the location of different stages of the production process is across multiple countries. This fragmentation of the production process means that intermediate goods pass the border of multiple countries, and sometimes of the same country, more than once. For China, insertion into GVCs initially involved mainly assembly of foreign inputs in China but has more recently transformed, with China now being a key supplier of production inputs to many Asian countries. This integration has allowed China's unprecedented growth over the last three decades to help lift all countries in the region. As China's final demand moderates, however, it may leave countries or sectors exposed to a decline in demand. In the case of Singapore, data shows that there were significant bilateral exports of GVC goods to China (Figure 2A) in 2022—equal to over 75 percent of Singapore's aggregate exports to China. At the same time, only 29 percent of Singapore's aggregate bilateral exports to China contains value-added that originates in Singapore (meaning the remainder of aggregate exports is content which is created in other countries, imported into Singapore, and either re-exported or used as intermediates to create Singapore's exports) (Figure 2B). This highlights the complicated task of understanding global spillovers in the context of complex GVCs.

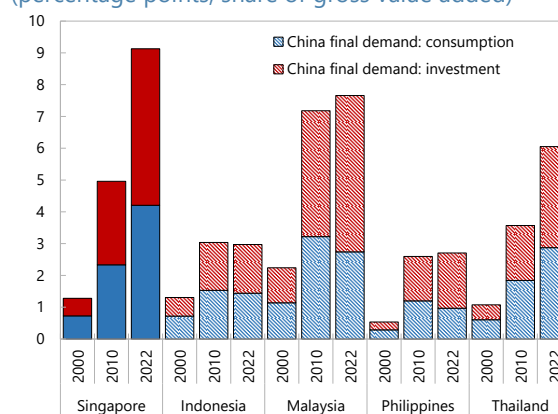


3. Given the domestic nature of China's structural transformation, final demand is expected to decline, leaving Singapore vulnerable. Both China's slowing productivity growth and its aging population are primarily domestic factors that will likely play out in a decline in final demand. Though trade in intermediate goods is a key aspect of regional flows, many countries in the region—and in particularly Singapore—have played an increasingly important role in serving Chinese final consumption and investment demand in the last two decades (Figure 3). Specifically, over 9 percent of Singapore's value-added in 2022 was ultimately absorbed by China, suggesting there is some value-added at risk in the face of China's structural transformation.

4. This paper seeks to estimate a range for the potential impact of a growth moderation in China on Singapore’s economy. Several approaches are taken which give a range of estimates and various perspectives of the possible magnitude and direction of spillovers. First, we look at the potential implications of a decline in growth in China on the value-added output of specific sectors in Singapore using global input-output tables. Here we identify the sectors in China which account for the largest share of Chinese final demand for Singaporean goods, and the sectors in Singapore which are the largest exporters of goods that are consumed as final demand in China. Then we turn to empirical analysis to estimate the expected spillovers. Using local projections methods, we estimate the impact of a decline in the Chinese GDP growth attributed to domestic factors on trend GDP growth in ASEAN countries, including Singapore. We then decompose Singapore’s trend GDP into its capital, labor, and total factor productivity (TFP) components and estimate the impact of a decline in Chinese growth on the growth of each component in Singapore. Lastly, we employ the IMF’s Global Integrated Monetary and Fiscal model (GIMF) augmented with GVCs to analyze the sensitivity of growth in Southeast Asia to growth shocks in China.

Figure 3. Singapore: Value Added Embedded in Chinese Final Demand

(percentage points, share of gross value added)



Source: EORA Global Supply chain Database; Aslan and others (2017); and IMF staff calculations.

B. Sectoral Impact of China’s Slowdown

5. Multi-region input-output tables can provide insights into a country’s exposure to Chinese final demand at the sectoral level. We employ multi-region input-output tables from the Eora Global Supply Chain database to study the sectoral linkages between China and Singapore. The table covers $c=189$ countries, $s=26$ intermediate good sectors, and $f=6$ final demand components over the years 1990-2022.² Several indicators, such as trade in intermediates or in final demand goods by origin, are extracted directly from the raw database, which is structured as

$$AX + Y = X \quad (1)$$

Where X is a matrix of gross output for each country, Y is the matrix of goods used for final demand, and A is the matrix of input-output coefficients, describing the units of intermediate goods needed to produce one unit of gross output. The Eora database provides data directly on X , Y and T where $T = AX$. Value-added indicators, including value added content of final demand (as well as

² The 6 final demand components are private consumption, public consumption, non-profit institutions serving households, gross fixed capital formation, changes in inventories, and acquisitions less disposals of valuables. See Lenzen and others (2012) and Lenzen and others (2013) for detailed description of the 26 sectors and their construction.

other measures such as backward and forward GVC trade) are constructed by recovering the A matrix from the raw data. We follow the steps laid out by Aslam and others (2015) and used in IMF (2023) for this procedure. Specifically, we first rearrange equation (1) such that $X = BY$, where

$$B = (I - A)^{-1}$$

is the Leontief inverse matrix. Each element of the B matrix shows the total output required directly and indirectly to produce one unit of goods for final demand, Y . Then A is recovered by using the T matrix of intermediate goods demand and the X matrix of gross output using the definition of $T = AX$ and element by element division of the T and X matrices:

$$A = T \oslash \begin{bmatrix} X' \\ \dots \\ X' \end{bmatrix}_{CS \times 1}$$

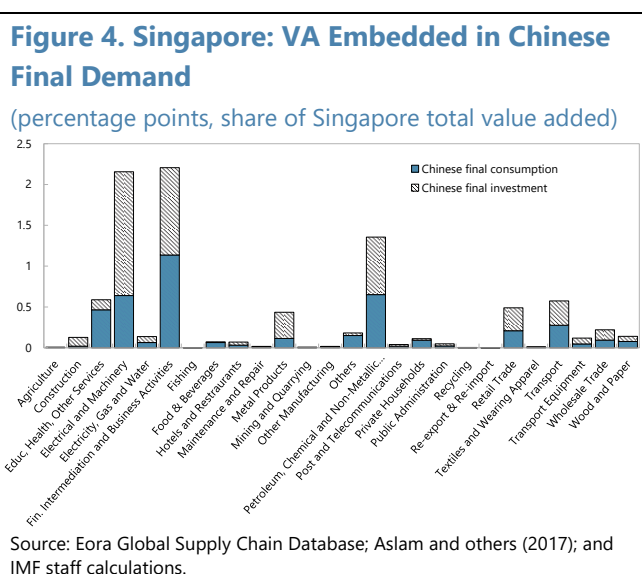
Finally, we calculate the foreign value added and domestic value added by recovering the matrix of value-added shares, \hat{V} , with our A matrix, as follows:

$$\hat{V} = I_{CS \times CS} - \text{diag} \left(\sum_i^{CS} A_{i1} \dots \sum_i^{CS} A_{iCS} \right)$$

where I is an identity matrix. See Aslam and others (2017) for more details on this derivation. Together, the $\hat{V}B$ matrix is the value-added shares matrix, meaning it contains all the information of value-added production by source that is embedded in the input-output table. Thus, to recover the value-added content from a source country in the final demand of a destination country we simply multiply $\hat{V}B$ matrix with final demand matrix, Y :

$$\text{Total value added} = \hat{V}BY = \hat{V}(1 - A)^{-1}Y \quad (2)$$

Because we are interested in final consumption and investment demand in China, we assume all other blocks of the Y matrix except those corresponding to columns for China are equal to zero, and in the final $\hat{V}BY$ matrix in (2) we extract the rows that correspond to goods whose value added originates in Singapore. This gives us Singapore's value added that is ultimately absorbed by China (even if it also passes through third countries).

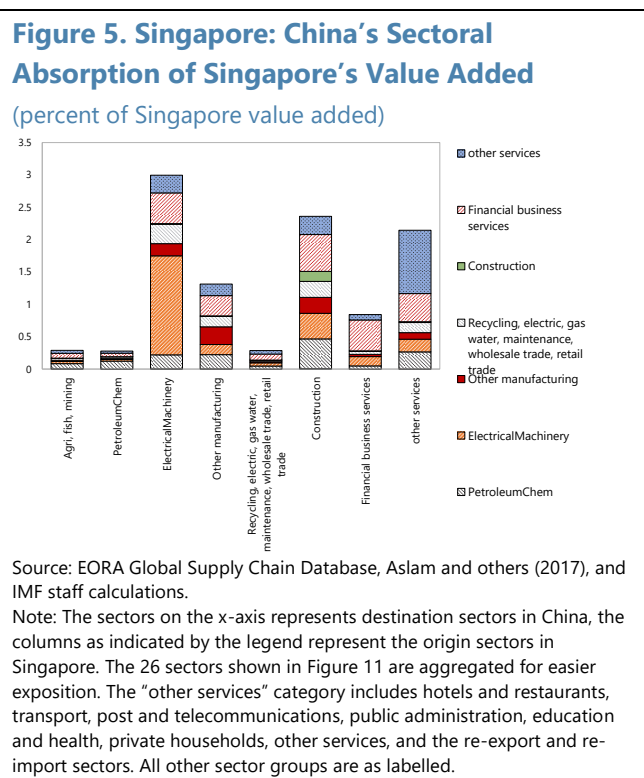


6. We find that Singapore’s value added that is ultimately absorbed in China is highly concentrated in a few industries. Our analysis shows that Singapore’s value added that is ultimately absorbed in China as final consumption and investment significantly increased over time to 9 percent of Singapore’s total value added (see paragraph 3 and Figure 3).³ We then decompose this value across the 26 origin sectors in Singapore and find that the financial intermediation and business services, electrical and machinery manufacturing, and petroleum and chemicals industries account for about 60 percent of Singapore’s value added that is ultimately absorbed by China (Figure 4, or 5.7 percentage points of the 9 percent of value added absorbed by China). In the business and financial services and in the petroleum, chemical and non-metallic mineral sectors, approximately half the value added goes to Chinese final consumption (both private and public) and half comes from Chinese final investment demand. In the electrical and machinery manufacturing sector, this demand comes primarily from Chinese final investment demand.

7. Chinese demand for Singaporean goods and services is also highly concentrated.

Singapore’s exports to China are absorbed in three main sectors in China—electrical and machinery equipment, construction, and financial and business services (Figure 5). Except for construction, a large share of the value added from Singapore absorbed in China remains within the same sector.

8. We construct a hypothetical scenario where Chinese final consumption and investment demand decline by 10 percent and examine the sectoral impact in Singapore. Since the global input-output tables allow us to examine both the flow of value added across countries and where value added created in one country is ultimately absorbed, we can also use the data to see how a decline in demand would be allocated across countries and sectors. We construct a hypothetical scenario where there is a 10 percent reduction in both Chinese final consumption and final investment demand across all country-sectors origins, and look separately at the impact of each decline. We use an approach similar to Los and others (2016), but



³ Note that while total value added in the global input-output tables is theoretically equivalent to GDP, in practice there is a degree of error in aggregating data to generate the tables and thus the two measures do not match exactly. In the case of Singapore, value added calculated from the EORA input-output tables ranges from 61 to 128 percent of actual GDP over the 1990-2022 period, with an average value of 91 percent of actual GDP. The correlation between the two series is 94 percent. We use the ratio of value added absorbed by China to total value added reported in the input-output table, rather than actual GDP, for consistency purposes.

rather than assigning the entire Chinese intermediate and final demand blocks of the Y and T matrices values of zero (as the authors do), we instead decrease their value by 10 percent. We call the intermediate goods demand and final demand matrices with these hypothetical values Y^* and T^* , respectively. We then calculate the corresponding hypothetical value added originating in Singapore that is absorbed in China in a similar way to equation (2):

$$\text{Total value added}^* = \widehat{V}(1 - A^*)^{-1}Y^* \quad (3)$$

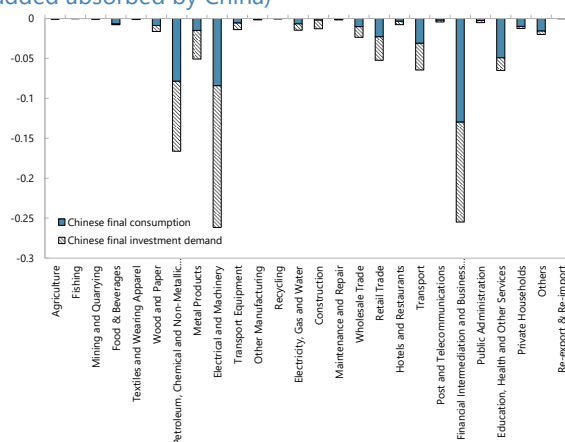
Because we are still only interested in final consumption and investment demand in China, we assume all other blocks of the Y matrix except those corresponding columns for China are equal to zero, and in the final $\widehat{V}BY$ matrix in (3) we extract the rows that correspond to goods whose value added originates in Singapore—as we did in equation (2). The difference between equations (3) and (2) is then the changes in value added originating from Singapore that is absorbed in Chinese final demand.

9. Results show that the source of the slowdown in China is important for spillover effects. Figure 6 shows the results of this exercise, separately for the decline in Chinese consumption and investment.

- The main sectors impacted—both by the decline in consumption and investment—are those who are initially most exposed to Chinese demand, that is the petroleum, electrical and machinery, and financial intermediation sectors. We calculate that the value added absorbed by Chinese final consumption and investment demand would decline by 0.15, 0.25, and 0.25 percentage points in each of these three sectors, respectively. The total decline across all sectors is equal to 1.1 percentage points.

Figure 6. Singapore: Impact of a 10 Percent Decline in Chinese Final Demand

(percent point difference in share of Singapore's value added absorbed by China)



Source: EORA Global Supply Chain Database; Aslam and others (2017); and IMF staff calculations.

- The source of the slowdown in China is also important. If it is a slowdown in final consumption, then those sectors in Singapore likely to see a bigger impact relative to an investment decline are services and household goods (food, clothing, textiles, education etc.). At the same time, these sectors represent less than half of Singapore's value added exported to China.
- Note that this exercise does not consider any behavioral response to the slowdown in China. On the upside, there would likely be some reorienting of exports to alternative destination that would offset the calculated decline. On the downside, the slowdown in China would translate into greater fragmentation in GVCs and lower demand for other goods and services that cannot be captured by the static input-output tables.

C. Aggregate Impact of China Growth Shock

10. This section analyzes the spillovers from China’s growth slowdown to ASEAN economies using aggregate cross-country data. After analyzing the sectoral linkages and their implication for spillovers, we now turn to provide an empirical estimate of the potential magnitude of these spillovers at the aggregate level, exploring also potential heterogeneity across ASEAN economies based on the intensity of trade ties with China.

11. In order to estimate the impact of Chinese growth on Singapore, exogenous domestic growth surprises must be first identified. Isolating exogenous domestic growth shocks in China ensures that in the second step of the analysis, where spillovers from these shocks are estimated, we are not capturing confounding effects (for instance global factors that would affect all countries simultaneously) but rather the change in China’s domestic growth alone. The methodology to identify domestically originated growth shocks in China follows Ahmed et al. (2022) by estimating the following regression:

$$\Delta \log Y_t = \beta_0 + \beta_1 X_t + \vartheta_t^{CHN} \quad (4)$$

where $\Delta \log Y$ is the first difference of the logarithm of China’s real GDP, sourced from the World Development Indicators (WDI). X is a vector of global factors including the change in the logarithm of global oil price, global metal price, the US long term bond yield and the real GDP growth of the G7 economies. These control variables are included contemporaneously following Ahmed et al. (2022). The US long term (10 years) bond yield is taken from the Federal Reserve Bank while the rest of the control variables are sourced from the IMF World Economic Outlook (WEO). ϑ_t^{CHN} —the residual of the regression—is then the China domestically originated growth shock. The intuition is that equation (4) purges the changes in Chinese real GDP that are driven by global factors, and isolates changes in Chinese GDP that depend only on domestic factors. This approach is also similar to Furceri et al (2017), although we focus on some specific global factors here.⁴ The approach, while simple, could over-estimate the growth shock if the specification (4) omits key global variables that are uncorrelated with the ones included. This is, however, unlikely given that growth for G7 countries is included among our controls. On the other hand, this could



⁴ Ahmed et al. (2022) also include in their VAR analysis the VIX, Emerging Market Bond Index, and growth of global imports excluding Asian EMs. We do not include these variables given limited data availability, which would severely reduce our sample size as we use annual data. We obtained similar shock series in robustness checks using a sample excluding the pandemic period.

underestimate the domestic component if changes in China’s real GDP are also a driver of our control variables. With that caveat, the China-domestic growth shocks estimated by equation (4) are presented in Figure 7.

12. The impact of China’s growth shock on ASEAN countries’ trend growth is then estimated using the local projection framework. Our empirical approach includes the 10 ASEAN economies over the period 1990-2019 and estimates the following two models, based on the local projection framework developed by Jordà (2005):

$$Y_{ct+h} - Y_{ct-1} = \beta^h \vartheta_t^{CHN} + \sum_{j=0}^5 \theta_j^h Z_{ct-j} + \alpha_c + \xi_{ct+h} \quad (5)$$

$$Y_{ct+h} - Y_{ct-1} = \beta^h \vartheta_t^{CHN} + \gamma^h (\vartheta_t^{CHN} \times G_{ct}) + \sum_{j=0}^5 \theta_j^h Z_{ct-j} + \alpha_c + \xi_{ct+h} \quad (6)$$

where Y_{ct} is the logarithm of the trend GDP of country c in year t , ϑ_t^{CHN} is the China-specific or China-domestic growth shock, Z_{ct} is a set of control variables including lags of China-specific growth shocks, G_{ct} , lags of trend GDP and lags of trade openness.⁵ α_c represents country fixed effects that control for unobserved country characteristics which do not vary over time. G_{ct} in equation (6) captures whether a country belongs to the high or low trade linkage group based on the sample median value. Countries with high (low) trade linkage are above (below) the sample median. Our specification in equation (6) follows the semi-parametric approach of Cloyne et al. (2023), providing a flexible way to estimate the impact of the China growth shock without any assumption about the functional form. The horizon, h , is up to five years. Equation (5) estimates the magnitude of the average growth spillovers to ASEAN country’s trend growth. Equation (6) estimates the same spillover but conditioning on the exposure to China through trade linkages. The variable of interest is trend growth, rather than actual growth, in order to capture the structural or long-term impact of a slowdown in China on ASEAN countries.⁶ The local projection approach offers several advantages, including robustness to misspecifications. Montiel Olea and Plagborg-Møller (2021) show that local projection inference is both simpler and more robust than standard autoregressive inference, whose validity is known to depend sensitively on the persistence of the data and on the length of the horizon.⁷

13. We find a statistically significant spillover from a shock to China’s domestic growth on average trend growth in ASEAN economies. Figure 8 shows that a 1 percentage point decline in China’s domestic growth could lead to an equal cumulative decline (about 1 percentage point) of

⁵ We obtain the trend GDP series based on HP filter applied to real GDP series. Trade openness data defined as total trade as share of GDP is taken from the World Development Indicators.

⁶ Note however that our idiosyncratic growth shocks from China potentially capture both structural and short-term dynamics. Using trend growth and a dynamic framework allows nevertheless to provide an assessment of the impact of these shocks on medium to long-term growth in ASEAN economies.

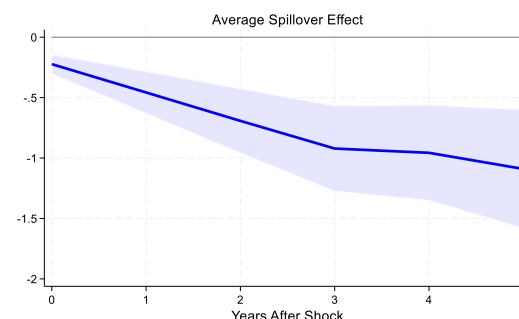
⁷ Note however that given our relatively short time dimension (with 30 years), the impulse responses could be biased especially over the longer horizon (Herbst and Johannsen, 2024). The issue could be mitigated by our short horizon of projection.

trend growth on average in ASEAN countries after five years, this is equivalent to about 0.2 percent per year. This estimate is within the range estimated by Dizioli et al (2016), who estimated an elasticity of Chinese growth on ASEAN-5 countries of about 0.2 percent over the period 1981Q1 to 2013Q1 using a GVAR model.

14. Our results also show that the magnitude of the spillovers is driven by strong trade linkages. Figure 9 shows larger spillovers for countries with stronger trade ties with China, either measured through gross trade or in value added terms. More specifically, the results show that the spillover is twice as large for countries with a stronger trade linkage with China. This is consistent with previous studies which have shown that the trade channel is the main channel of transmission of growth spillovers from China (Duval et al., 2014; Furceri et al, 2017, Copestake et al, 2023). However, for Singapore, the more relevant channel appears to be related to its relative dependence on final demand from China in value-added terms (as implied in Figure 3). More specifically, the estimates imply a cumulative impact of 2.1 percentage points over five years in Singapore, compared to 1.4 percentage points for the average ASEAN country in the sample over the period, given its dependence on Chinese final demand (Figure 10).

Figure 8. Singapore: Average Spillover of China's Growth on ASEAN Countries Trend Growth

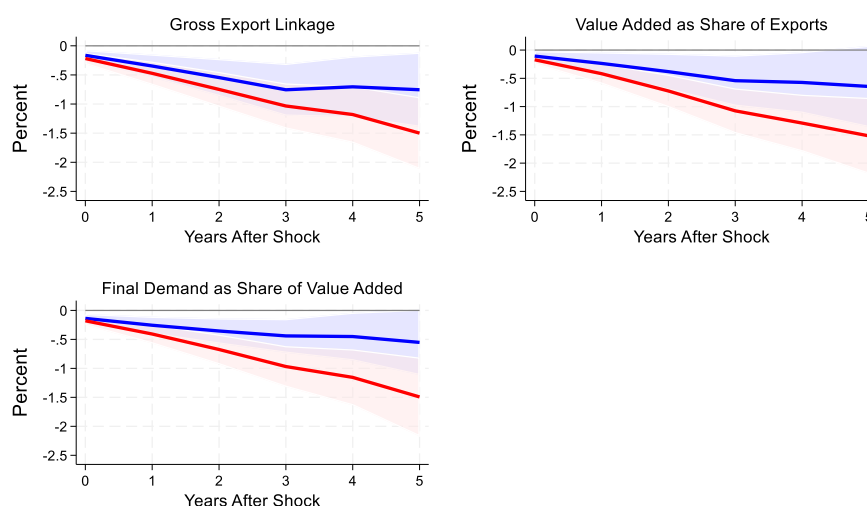
(percentage point)



Source: IMF staff calculations.

Note: This chart shows the average impact of a 1 percent reduction in Chinese GDP shock on trend output growth in ASEAN countries. 90 percent confidence interval from Kraay and Driscoll standard errors in shaded areas. Marginal Impact is in percent. China shock is identified based on equation (1).

Figure 9. Singapore: The Trade Channel of Growth Spillovers from China to ASEAN Countries



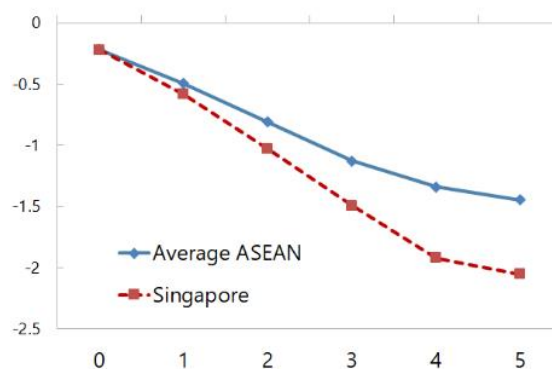
Source: IMF staff calculations.

Notes: This chart shows the impact of 1 percent reduction in Chinese GDP domestic growth shock on trend output growth in ASEAN countries. The red (blue) lines show the marginal impact for ASEAN countries with high (low) gross trade of value-added linkage with China. Gross export linkage is obtained as exports to China in share of total Exports. We calculate value added linkage in two ways, i) as the share of value-added exports to China in total exports and ii) the share of final demand from China in total value added. 90 percent confidence interval from Kraay and Driscoll standard errors in shaded areas. Marginal Impact is in percent.

Figure 10. Singapore: Dependence on Final Demand from China and Growth Spillovers

(Percentage point, marginal effect on trend output)

Sources: Eora Global Supply Chain Database; and IMF staff calculations.



Sources: Eora Global Supply Chain Database IMF Staff Calculations

Notes: The coefficient estimates are obtained from a specification similar to Equation (6), however we interact the China growth shock with the level of final demand from China in ASEAN countries. We then calculate Singapore-specific marginal impact by multiplying the coefficient by the average final demand in value added over the period (1990-2019).

15. We find that growth spillovers from China to ASEAN countries is likely to be driven by the impact on investment and to some extent employment. In a simplified Cobb-Douglas production function approach, output growth can be written as:

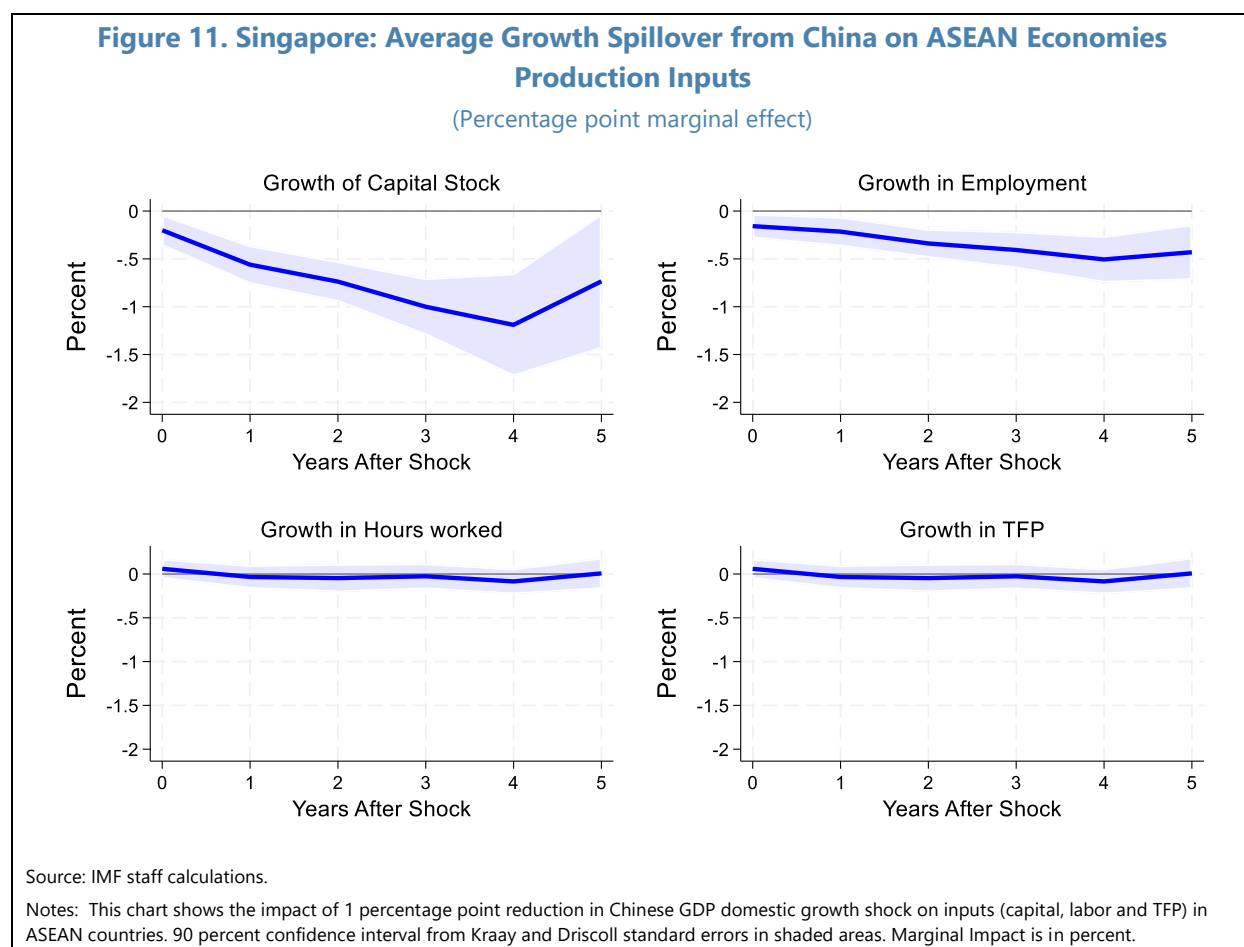
$$g_y = g_{TFP} + (1 - \alpha)g_K + \alpha g_L$$

where, g_{TFP} is total factor productivity (TFP) growth, g_K is capital growth, g_L is labor growth, and α is labor income share. We take data on TFP, capital stock, and employment (both number of persons employed, and average number of hours worked) from the Penn World Tables and estimate how growth spillovers from China affect these determinants of output. Our estimates, using a specification similar to the one in equation (5), but instead using labor, capital, and TFP as dependent variables, are shown in Figure 11. The results show that domestic growth shocks from China are likely to impact trend output in ASEAN economies first through their impact on capital stock and, in a more moderate way, through their impact on employment. We find that a 1 percent decline in the China domestic growth shock could decrease capital stock in ASEAN economies cumulatively by 1 percentage point over 4 years before moderating to about 0.8 percentage points in the fifth year. The impact is about 0.5 percentage points cumulatively over five years for employment. We find no meaningful impact on hours worked and on TFP. Overall, our results imply that growth spillovers from China to trend output in ASEAN economies are likely to be particularly strong through the impact on investment. Indeed, expectations about the growth prospects of an important trade partner such as China is likely to affect firms' decision to invest in their productive capacity, which would ultimately translate into trend output. Macroeconomic model simulation in the next section looks in more detail at this channel.

16. Our finding on the size of the spillovers is robust to using an alternative measure of the size of the China-specific growth shock. In an alternative approach, we estimate the China-specific growth shock, following Furceri et al. (2017) as follows:

$$\Delta \log Y_{ct} = \beta_c + \tau_t + \varepsilon_{ct} \quad (7)$$

where $\Delta \log Y_{ct}$ is the change in the log of real GDP in country c at time t ; β_c are country fixed effects; and τ_t are time fixed effects. We estimate this panel specification for China and all ASEAN countries in the sample and obtain ε_{ct} for c =China, as the China-specific growth shock. While Figure 12 shows that the baseline shocks were potentially under-estimating China specific growth, the results from the estimated spillovers reported in Figure 13 are very similar to our baseline results. Specifically, we find that, on average, a 1 percent increase in China's growth could lead to persistent spillovers to growth in ASEAN, resulting in a cumulative increase of about 0.8 percentage points over five years. This translates to an average annual growth impact of 0.16 percent (close to the 0.2 percent in our baseline estimation).



D. A General Equilibrium Analysis of Spillovers from China's Growth to Southeast Asia

17. A general equilibrium framework can facilitate studying the spillovers from shocks in an interconnected world. This section uses the IMF's Global Integrated Monetary and Fiscal model (GIMF) augmented with GVCs to analyze the sensitivity of growth in Southeast Asia to growth shocks in China.⁸ GIMF is IMF's multi-regional micro-founded dynamic stochastic

general equilibrium (DSGE) model. In the model, firms produce two types of intermediate goods, tradeable or non-tradeable, with the former consumed domestically and exported. Final goods are an inelastic combination of tradeable and non-tradeable goods. The model has 10 regions, including the United States, EU and Switzerland, other advanced economies, China, India, Indonesia, Japan, South Korea, other Southeast Asia (which includes Singapore), and the rest of the world.⁹ Bilateral trade between each region is tracked.

18. GVCs lead to a greater complexity in the trade linkages between countries and are accounted for in the GIMF model. To account for the complex trade interlinkages, as detailed in

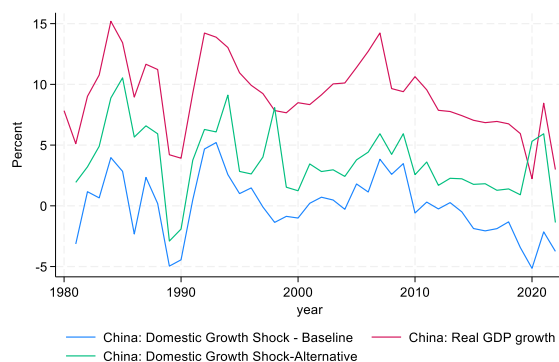
Carton and Muir (forthcoming), the GIMF model is augmented with GVCs. This extension disaggregates the tradeable goods into non-GVC tradable goods and GVC tradable goods. GVC goods can be used domestically as intermediate goods to produce other GVC goods, or they can be exported. Domestically produced GVC goods can also be combined with non-GVC tradeable goods to form an aggregate tradable intermediate goods bundle. The final goods produced domestically are a combination of non-tradeable and tradeable intermediate goods. If traded, the GVC goods can

⁸ The exercise draws on IMF (2023) and Cerdeiro et al. (forthcoming).

⁹ Other Southeast Asia comprises Brunei, Cambodia, Hong Kong SAR, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam. The version of the model used for this study does not disaggregate these countries, consequently masking the heterogeneity in their direct and indirect linkages to China.

Figure 12. Singapore: Alternative China Growth Shock

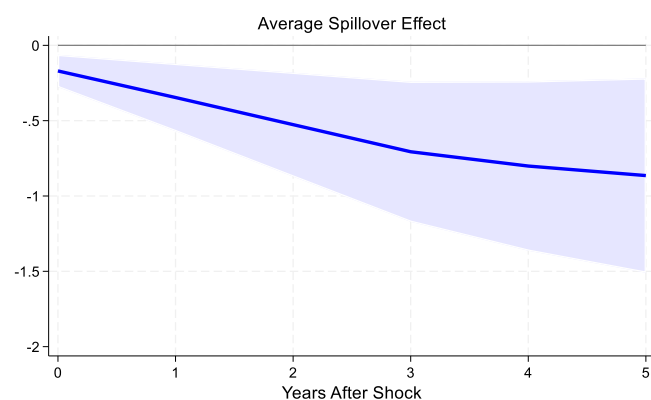
(percentage point)



Source: IMF World Economic Outlook; and IMF staff calculations.

Figure 13. Singapore: Robustness Check – Average Spillover from China Growth on ASEAN Trend Growth

(percentage point)



Source: IMF staff calculations.

Notes: This chart shows the average impact of a 1 percent increase in Chinese GDP shock on trend output growth in ASEAN countries. 90 percent confidence interval from Kraay and Driscoll standard errors in shaded areas. Marginal Impact is in percent. China shock is identified based on equation (4).

again be used as intermediates to produce additional GVC goods or as final products. Thus, the extended GIMF model with GVCs can capture the complex linkages of non-tradable, non-GVC tradable, and GVC tradable production sectors, within and across countries, including through round-about trade.

19. The model is calibrated to match data that shows Southeast Asia is one of the most open regions in the world. Each region in the model is calibrated using OECD Inter-Country Input-Output Database of 2018. The model's steady-state calibration implies that Southeast Asia, excluding Indonesia, is one of the most open regions in the world, with exports and imports accounting for about 60 percent of GDP. Moreover, the region is also highly integrated in GVCs, with GVC tradable exports accounting for about 40 percent of aggregate exports and GVC tradable imports accounting for about 50 percent of aggregate imports. This implies that the region is very sensitive to shocks on GVC tradable sectors. While the model is calibrated to the broader Southeast Asia region, relative to the region, Singapore is more open and more deeply integrated in GVCs (recall Figure 2), including due to the large share of electrical and electronic products in its trade. This suggests that the simulated impact on the region from a downside scenario may underestimate the possible impact of the shock on Singapore. The calibration also assumes a relatively inelastic demand for goods in the GVC tradable sector, based on an assumption that the cross-sector and cross-region chains are more difficult to reconfigure. This means that for regions more dependent on GVC goods, shocks will lead to larger movements in prices.

20. Simulations suggest significant growth spillovers to Southeast Asia from productivity shocks in China. We consider a scenario in which China's aggregate annual productivity grows by about 1 percentage point higher relative to the baseline for 15 years.¹⁰ Moreover, it is assumed that in China's GVC sector, productivity grows twice as fast as the productivity growth in the non-tradables sector to account for the large productivity gaps relative to the frontier in the GVC sector (IMF, 2023). The model can capture both the direct spillovers from trade linkages and productivity spillovers from China to other regions, with the latter accounting for both direct technological spillovers from the technology content in imports and indirect spillovers from dissemination of technological advances. Estimates are presented in Figure 14, which suggest that in this scenario where China's GDP level in the long-run increases by over 20 percent, GDP level in Southeast Asia (excluding Indonesia) increases by over 4 percent, relative to baseline. The increase in productivity in China results in greater investment (Figure 14, panel B) and capital stock, as the higher productivity implies a larger return to capital. Labor demand also increases, resulting in an increase in labor income and consumption (Figure 14, panel C), which supports a stronger growth in China. As China and Southeast Asia (excl. Indonesia) have strong trade ties, this leads to greater external demand that bolsters growth in the region.

21. Strong spillovers to growth in Southeast Asia can also be explained through indirect technological spillovers and the region's strong integration in GVCs. Indirect technological

¹⁰ We show the impact from a positive shock in line with IMF (2023), Cerdeiro and others (forthcoming), and Carton and Muir (forthcoming). One can imagine the impact of the equivalent negative shock to Chinese productivity as having results of the opposite sign, though due to the nature of the model they would not be exactly symmetric.

spillovers lead to an increase in productivity in Southeast Asia (excl. Indonesia), causing private investment and consumption in the region to grow as well. Such technological spillovers are larger for regions that have stronger trade ties with China and that are further away from the technological frontier, as is the case for Southeast Asia (excl. Indonesia) (see IMF, 2023). Additionally, increased productivity in the GVC sector in China leads to a decline in prices of GVC goods and an increase in their demand both domestically and abroad (Figure 14, panel E). Since Southeast Asia is also strongly integrated in GVCs, particularly with China, the region benefits from greater demand for GVC goods.

E. Summary

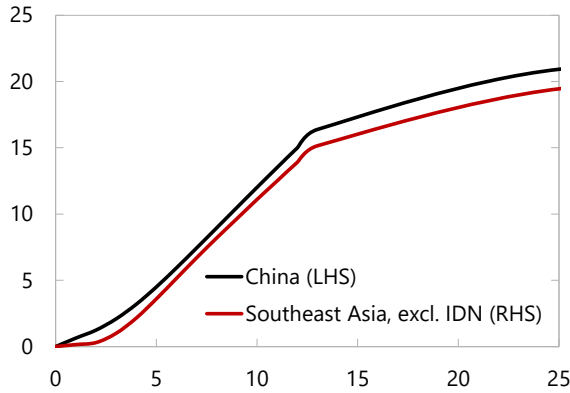
22. Growth in China is expected to moderate over the medium term. According to IMF staff projections, ageing population and slowing productivity growth are projected to lower China's GDP growth to around 3.5 percent by 2028. This is expected to happen from a moderation in both investment and consumption.

23. We find that this slowdown will likely have important spillovers to ASEAN countries, including Singapore. We first take a detailed look at the sectoral exposure of Singapore's value added to China and find that those sectors most exposed to China (electrical and machinery, petrochemical, and financial intermediation) will likely account for much of the decline in production in the face of moderating Chinese growth. Using a local projection method to capture the dynamic impact of such a domestic growth shock, we estimate that a 1 percentage point decline in Chinese domestic growth will result in a cumulative decline of about 1 percentage point of trend growth on average in ASEAN countries after five years, which is equivalent to about 0.2 percentage points per year. Accounting for the particularly large exposure of Singapore to Chinese final demand (relative to other ASEAN countries) suggests the cumulative decline in Singapore's output could be as high as 2.1 percentage points over five years. The decline will come primarily from a drop in the growth of capital stock, and to a lesser extent from a decline in employment growth, while TFP growth is not expected to be significantly affected. A general equilibrium model analysis provides further evidence of the spillover channels from China to Singapore and ASEAN peers, showing that productivity driven growth shocks in China may have a significant impact on the region's growth due to trade linkages and that these spillovers are amplified by the region's deep integration in GVCs.

Figure 14. Singapore: Spillovers from China's Growth to Southeast Asia

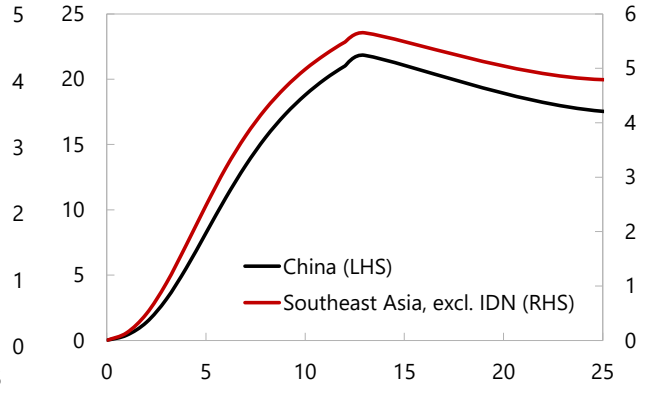
A. Real GDP

(percent deviation)



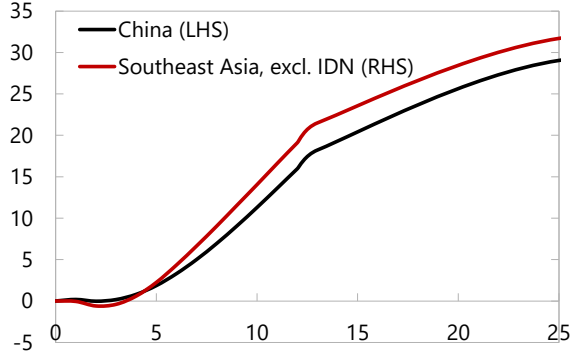
B. Real Private Investment

(percent deviation)



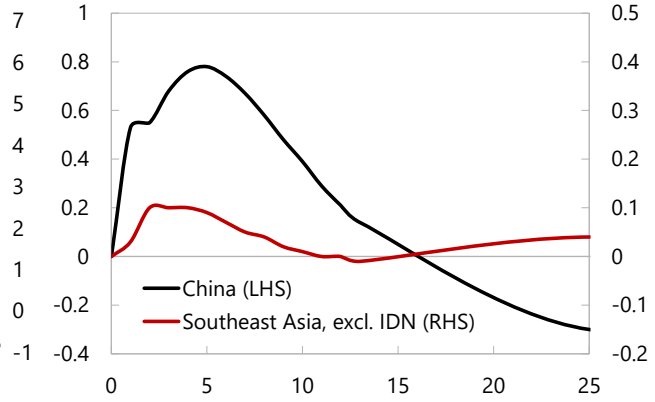
C. Real Household Consumption

(percent deviation)



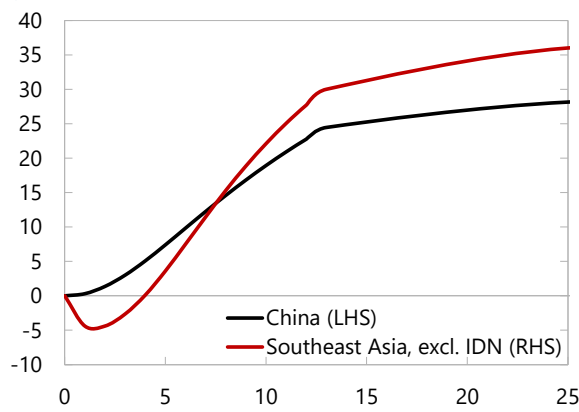
D. Trade Balance/GDP

(absolute deviation)



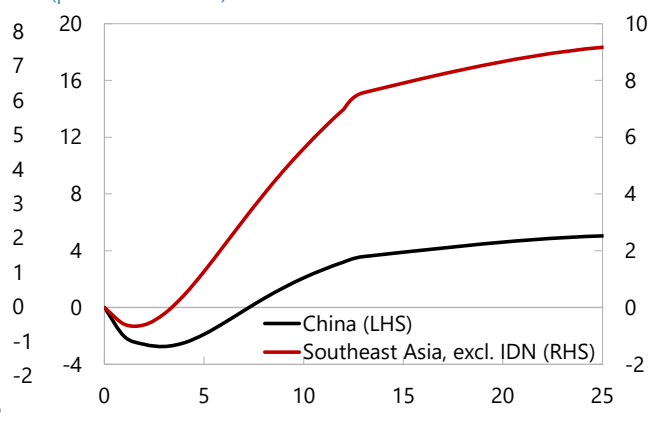
E. Real Exports of GVC Goods

(percent deviation)



F. Real Imports of GVC Goods

(percent deviation)



Source: IMF (2023) and IMF staff calculations.

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IMPACT OF AI ON SINGAPORE'S LABOR MARKET¹

Singapore is well-prepared for AI adoption but stands highly exposed to the increasing use of artificial intelligence (AI) technologies in the workplace, due to a large share of skilled workforce. While half of the highly exposed segment of the labor force stands to benefit from the appropriate use of AI to complement their tasks, potentially boosting their productivity, the other half may face greater vulnerability to AI's disruptive effects due to lower levels of AI complementarity. Estimates suggest that women and younger workers are more exposed to the effects of AI, which, in the absence of appropriate policies, could worsen income inequality in Singapore. Targeted training policies, leveraging on the existing SkillsFuture program, can harness AI's potential. Additionally, focused upskilling can mitigate the disruptive impact of AI on vulnerable workers.

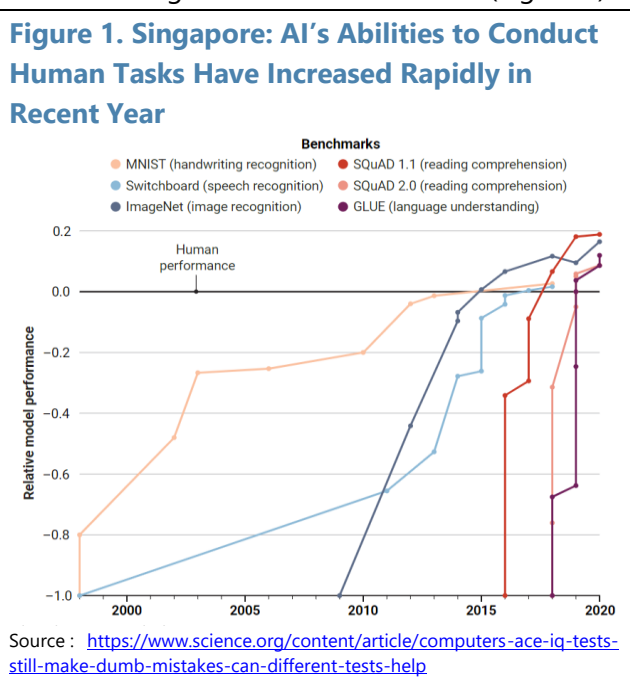
A. Introduction

1. Artificial intelligence (AI) has been rapidly advancing in its abilities to conduct human tasks. In recent years, the pace of development in AI technologies has been remarkable (Figure 1).

This progression is evident in the increasing sophistication of AI systems, which are now able to undertake a wide array of activities, ranging from simple data entry to complex text comprehension and problem solving. As these technologies evolve, they are increasingly mimicking human intelligence and behaviors, thereby blurring the lines between human and machine capabilities. This shift is transforming various industries, as AI applications become more prevalent and adept at executing tasks that were once considered exclusively within the purview of human expertise.

2. Singapore is well-prepared for AI adoption. The IMF's AI Preparedness Index (AIPI) evaluates AI readiness in 174 countries

using a comprehensive set of macro-structural indicators, including digital infrastructure, human capital and labor market policies, innovation and economic integration, and regulation and ethics.² Singapore excels across all these indicators, underscoring its strong readiness for AI integration. This reflects Singapore's investment in robust digital infrastructure, which ensures seamless connectivity and supports advanced AI technologies.



¹ Prepared by Shujaat Khan.

² See <https://www.imf.org/external/datamapper/datasets/AIPI>.

3. AI technologies are expected to change the way we work, which will have implications for labor markets around the world.

As AI proliferates the workspace, it brings with it the potential for increased productivity and efficiency, but it also raises concerns about the displacement of workers whose tasks can be automated with limited human intervention. This dual-edged nature of AI's integration into the workforce necessitates a careful examination of its impact on labor markets, balancing the benefits of enhanced productivity against the risks associated with job losses and the need for workforce adaptation. Furthermore, the impact of AI on the workforce is likely to vary across different demographics, influenced by the extent to which various occupations are exposed to AI integration and how these occupations are distributed among different genders and age groups. Therefore, tailoring policy responses to harness the benefits of AI while mitigating the adverse effects that could lead to increased income and wealth inequality is crucial to ensuring equitable outcomes across all segments of society.

4. This study utilizes estimates of AI exposure and complementarity to study the impact of AI on Singapore's labor market.

Following Felten et al. (2021), we make use of a micro approach that links AI's applications to the workplace abilities required in different occupations to estimate each occupation's exposure to AI (Section B), which reflects the potential for AI to be integrated into that occupation. To allow for a distinction to be made between occupations for which AI has the potential to complement or to reduce the demand for labor, we also use estimates of potential AI complementarity for various occupations from Pizzinelli et al. (2023). Detailed labor force data is used to estimate occupation-level exposure to AI in Singapore (Section C) and to examine how the exposure differs among various demographic groups (Section D). Policies that harness the benefits of AI, while mitigating its adverse effects, are also discussed (Section E).

B. Measuring Occupational Exposure to AI

5. A micro approach that links applications of AI to workplace abilities can be used to study the occupational exposure to, or potential for integration of, AI.

AI exposure for a particular occupation measures the extent to which AI has a potential to be integrated in the occupation. This study relies on estimates of occupational exposure to AI produced by Felten et al. (2021) that links 10 common applications of AI (for example, abstract strategy games, image recognition, speech recognition)³ to a range of workplace abilities and occupations. A total of 52 workplace abilities (covering cognitive, physical, psychomotor, and sensory abilities) are considered. O*NET, a database developed by the US Department of Labor, uses these abilities to define every occupation (up to 8-digit level based on the Standard Occupational Classification (SOC) system) based on the workplace activities of each occupation. Using survey responses from gig workers on Amazon's Mechanical Turk (mTurk) platform, Felten et al. (2021) link each AI application to various workplace abilities based on whether the respondents believe that the application is related to or could be used for each workplace ability. If we define x_{ij} as the relatedness score of AI application $i \in \{1, \dots, 10\}$ and occupational abilities $j \in \{1, \dots, 52\}$, then the ability-level AI exposure is given by $A_j = \sum_{i=1}^{10} x_{ij}$. This ability-level AI exposure, combined with weights for the prevalence and

³ The 10 AI applications considered by Felten et al. (2021) are: abstract strategy games; real-time video games; image recognition; visual question answering; image generation; reading comprehension; language modeling; translation; speech recognition; and instrumental track recognition.

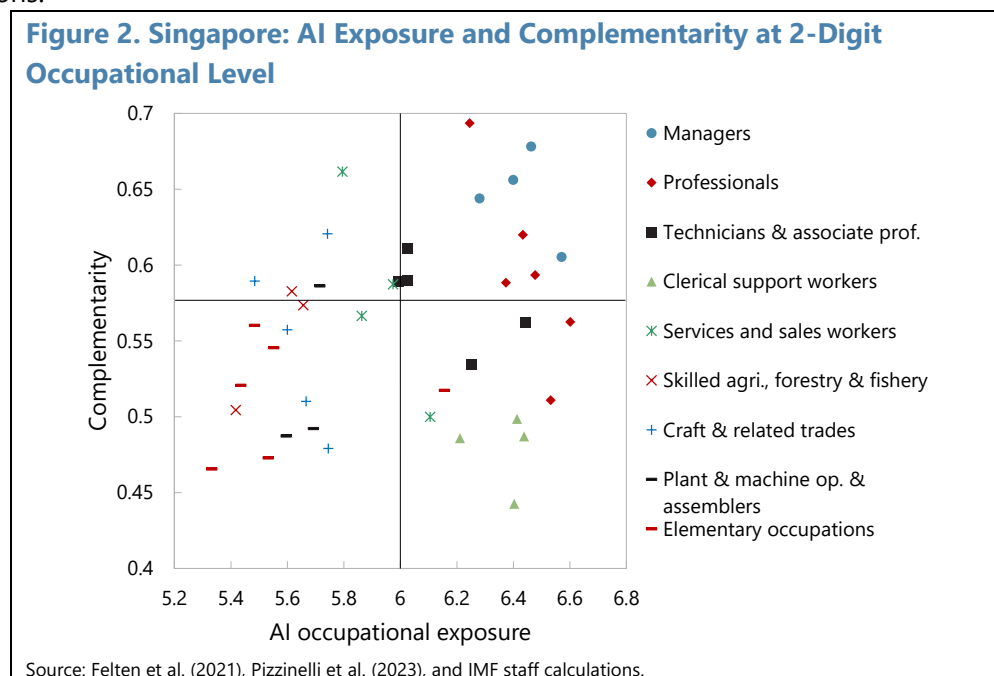
importance of the abilities in each occupation, which are also available in O*NET's description of occupations, is used to calculate the exposure of each occupation to AI. This is referred to as AI occupational exposure (AIOE).

6. In addition to understanding exposure to AI, it is also important to evaluate whether AI might augment worker capabilities or diminish labor demand. AI complementarity for a particular occupation measures the extent to which AI can complement human labor in the occupation. We use estimates of AI complementarity from Pizzinelli et al. (2023), which utilizes data related to work contexts and skills of occupations from the O*NET database. Work contexts encompass both the social and physical dimensions of performing tasks within specific occupations. Factors such as the significance of decision-making and the severe implications of mistakes are job characteristics that could prompt the insistence on human oversight for final judgments or interventions. Pizzinelli et al. (2023) use case-by-case assessments to argue that certain contexts might deter societies from allowing unsupervised autonomous use of AI. Skills, on the other hand, are defined by the level of education, on-the-job training, and professional experience needed to perform a job. The consideration of skills stems from the notion that jobs demanding more extensive professional development are better positioned to incorporate AI knowledge into their training, thereby preparing workers with skills that complement AI.

7. Taken together, occupational exposure to and complementarity with AI offer deeper insights on the potential impact of AI on different jobs. We define an occupation as having high (low) AI exposure or complementarity if it has an AI exposure or AI complementarity score above (below) the median for all occupations. Estimates of AIOE reveal a complex and varied landscape across different occupations (Figure 2). While the workers in the high-exposure and high-complementarity occupations are expected to witness gain in productivity from the appropriate use and integration of AI, the workers in high-exposure and low-complementarity occupations are at a greater risk of being displaced by AI. AI complementarity is less relevant for occupations with a low AI exposure; therefore, the focus of this work is on occupations that have a high level of exposure. Based on these estimates, at the aggregate (1-digit) level, high-skilled occupations, such as managers, professionals, and technicians and associate professional, tend to have a higher exposure to AI (that is, the AIOE score is greater than the median AIOE score). In contrast, low-skilled occupations, such as elementary occupations, plant and machine operators and assemblers, craft and related trade workers, and skilled agriculture, forestry and fishery workers tend to have a lower exposure to AI. Semi-skilled roles such as clerical support workers are estimated to be highly exposed to AI, whereas services and sales workers demonstrate a mix of high and low AI exposure, depending on the specific job within that group.

8. There is significant variation of AI complementarity both across and within occupational categories. While at the aggregate (1-digit) level, generally, the sub-occupations (2-digit level) are within the same AI exposure classification (high vs. low), there is significant variation within each major occupation based on the level of complementarity of AI in those roles. For instance, professionals tend to have a high exposure to AI; however, some jobs within this category exhibit high complementarity (for example, health professionals) and others exhibit low complementarity (for example, information and communication technology professionals). Nonetheless, there are also high-exposure occupations that are either entirely (at the 2-digit level) in

the high-complementarity classification (managers) or are entirely in the low-complementarity classification (clerical support workers, elementary occupations). Workers in managerial roles, who typically have high skill-level and greater experience, benefit from the higher degree of complementarity, while workers in clerical support positions, such as general and keyboard clerks and customer service clerks, are in roles that offer a lower degree of complementarity. Since elementary occupations, and plant and machine operators and assemblers, craft and related trade workers, and skilled agriculture, forestry and fishery workers have low exposures to AI, the level or variation in complementarity is less important in determining the impact of AI for workers in these occupations.



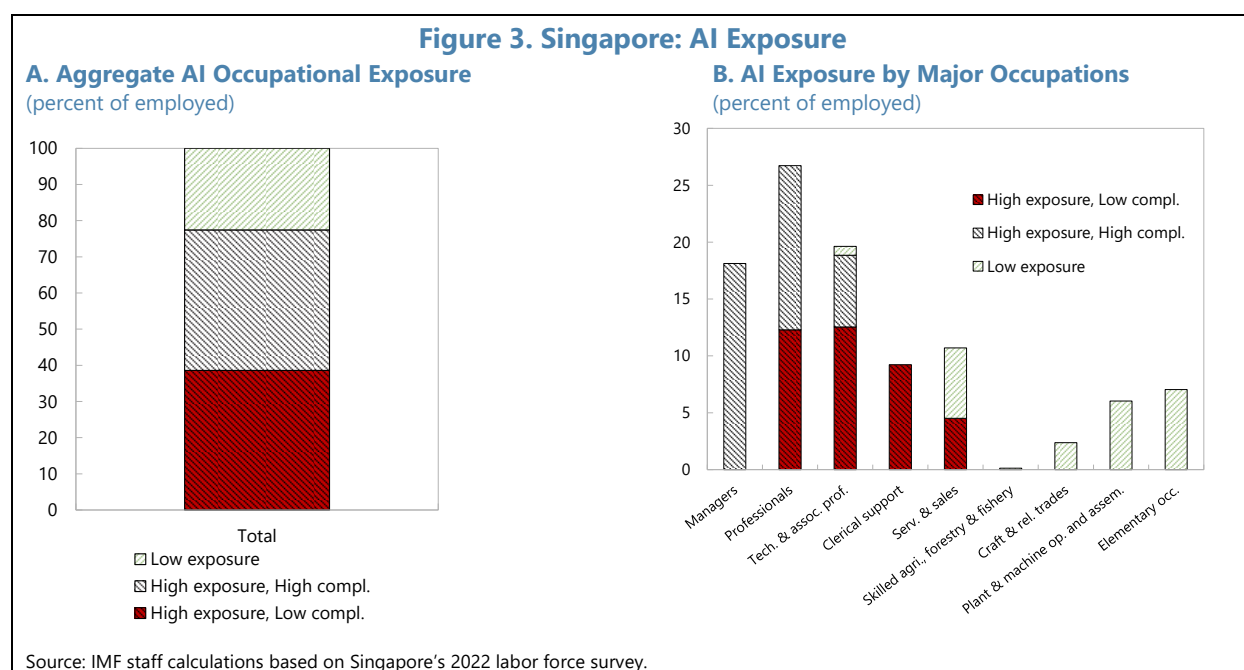
C. AI Exposure in Singapore's Labor Market

9. Singapore's labor market is highly exposed to AI, driven largely by the concentration of high- and semi-skilled workers in its workforce. Estimates, based on Singapore's 2022 labor force survey of resident workers, show that about 77 percent of Singapore's employed workers are highly exposed to AI (Figure 3A), that is, a significantly large share of workers are working in occupations that have a high potential for AI to integrate into their occupations. This exposure not only surpasses the average high exposure rates of 40 percent for emerging market economies (EMs) and 26 percent for low-income countries (LICs), as estimated by Cazzaniga et al. (2024), but also exceeds the AI exposure rate of 60 percent estimated for advanced economies.⁴ Singapore's high AI exposure largely stems from a minimal portion (about 23 percent of employed) of its workforce being employed in low-skilled jobs—in contrast to the larger shares seen in emerging markets (EMs)

⁴ Note that the exposure estimates for Singapore are based on labor force data covering only resident workers.

and low-income countries (LICs)—coupled with a substantially larger proportion of individuals working in high- and semi-skilled roles.

10. Within occupations highly exposed to AI, there is an equal distribution of workers between roles that exhibit high and low complementarity with AI. Of those workers who are highly exposed to AI, roughly half (38.9 percent of employed) are in occupation with high AI complementarity and the other half (38.6 percent of employed) have jobs with low AI complementarity. The former mainly comprise managers, science and engineering, health, and legal professionals and associate professionals, and teaching professionals. These workers stand to gain in productivity, provided they have access to the required infrastructure and possess the necessary skills to interact with AI technologies effectively. In contrast, business and administration, and information and communications technology professionals and associated professionals, clerical support workers, and a fraction of services and sales workers are at a higher risk of substitution due to AI’s abilities to mimic or automate the tasks required in those jobs.

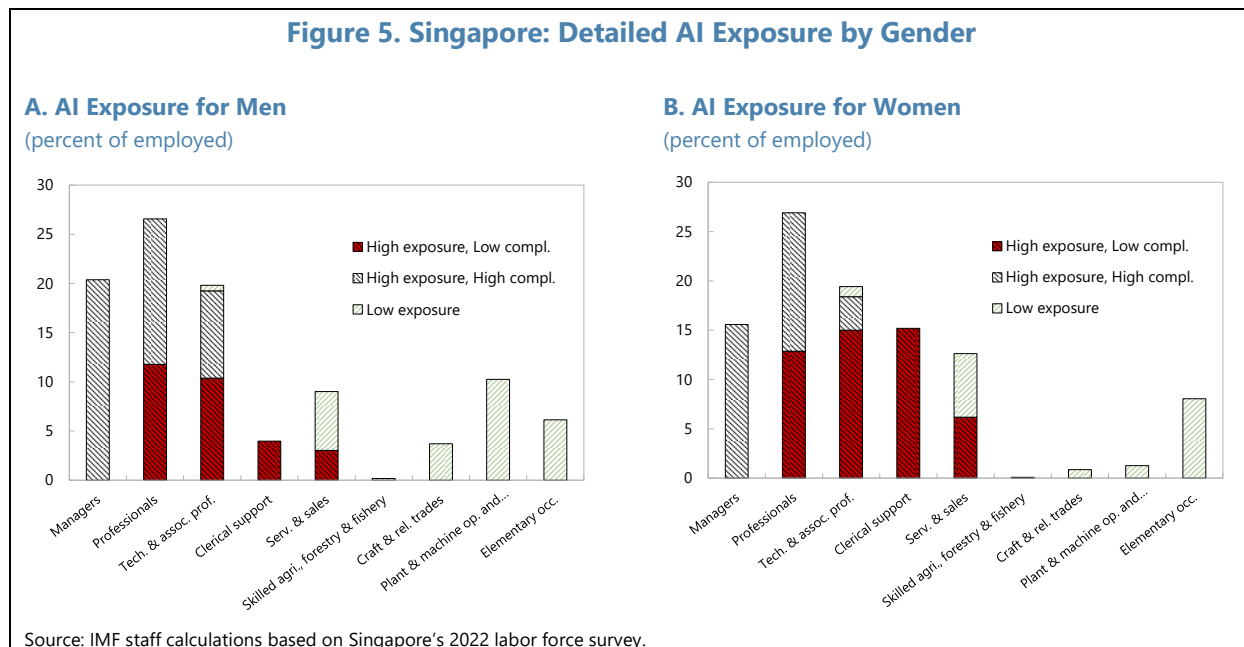
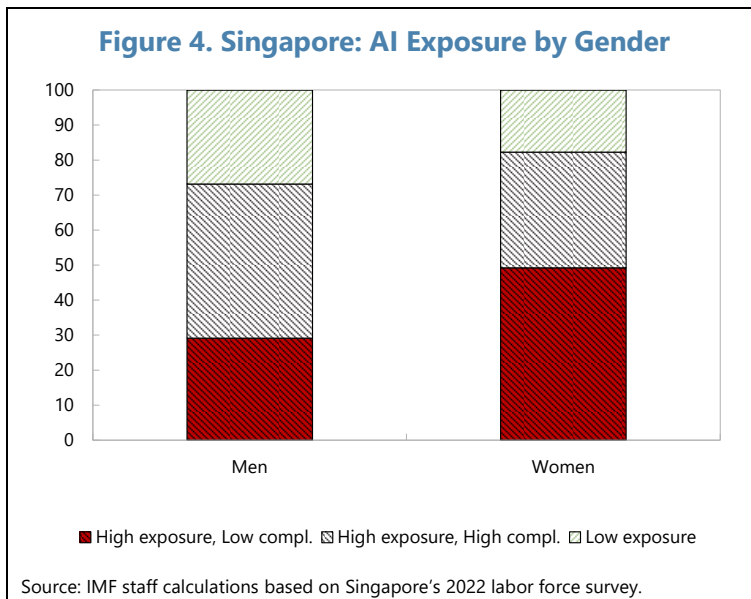


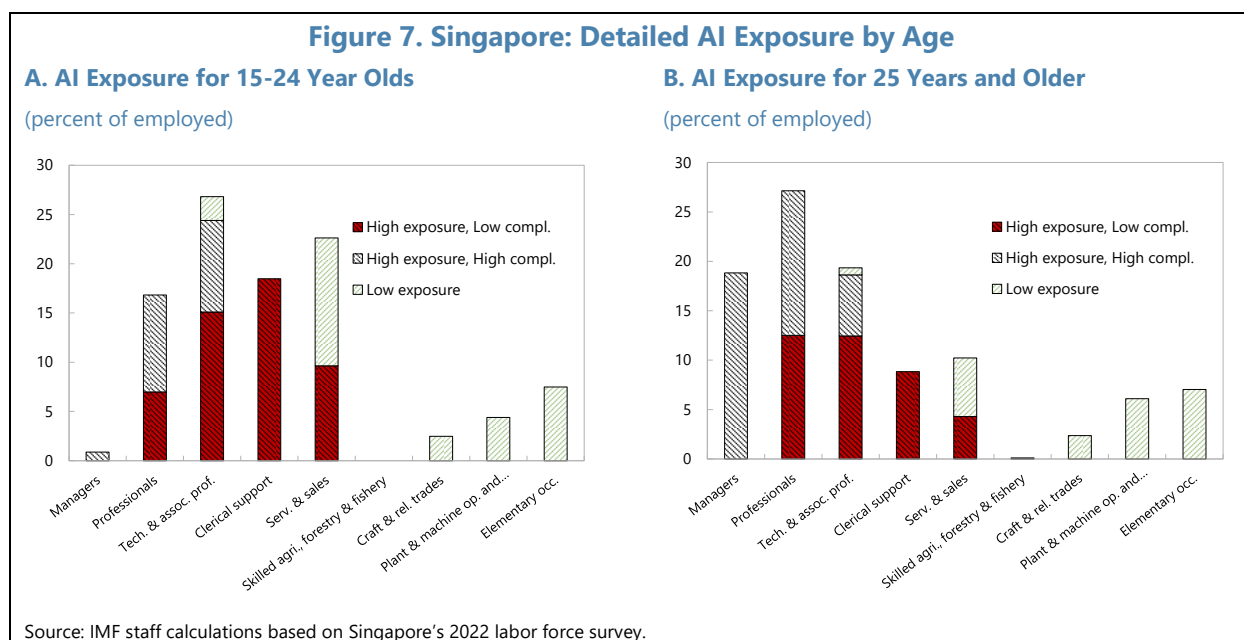
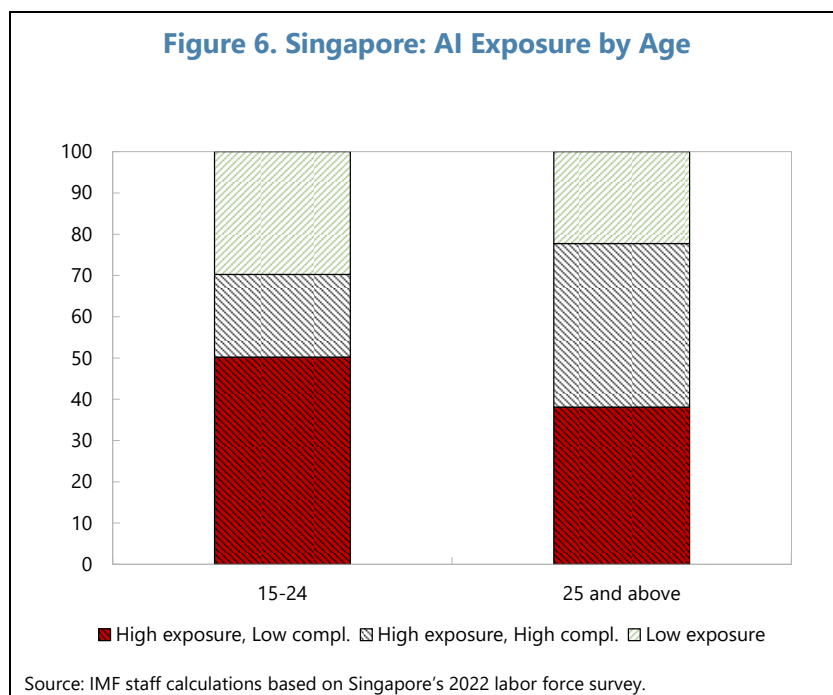
D. Demographic Implications

11. Our results suggest that female workers in Singapore have a higher exposure to AI with relatively low AI complementarity. Estimates suggest that a larger fraction of female workers are exposed to AI, particularly in occupations which have low complementarity with AI (Figure 4). About 49 percent of female workers are employed in occupations that have a high exposure and low complementarity with AI, compared to 29 percent of male workers falling in the same category. These differences largely stem from a larger share of female workers employed in clerical support roles (15 percent, relative to men’s 4 percent employment share) and a larger share of women employed as business and administration associate professionals (14 percent, relative to men’s 9 percent employment share) and sales workers (6 percent, relative to men’s 3 percent employment

share), all of which have a high exposure to and low complementarity with AI. In addition, a significantly higher share of men is employed in high exposure occupations that also have a high complementarity with AI (44 percent, relative to women's 33 percent employment share). This is driven by the greater share of men employed as managers (20 percent, relative to women's 16 percent) and science and engineering associate professionals (7 percent, relative to women's 2 percent employment share), occupations which stand to benefit from increased productivity due to AI augmentation. These differences have the potential for widening gender gaps with a widespread adoption of AI technologies in work.

12. Younger Singaporean workers are employed in occupations with a higher susceptibility to displacement due to AI. Although the occupational employment data by age in this study only permit a broad differentiation between age categories, they still enable us to draw some valuable inferences. About 6 percent of the workers are between 15 to 24 years old and the remaining workers are 25 years and older. Estimates suggest that half of the younger workers are employed in occupations with high AI exposure and low AI complementarity and only one-fifth of the young workers are employed in occupations with high AI exposure and high AI complementarity (Figure 6). A higher percentage of younger workers are found in clerical support positions and sales jobs compared to their older counterparts. Moreover, a smaller proportion of young workers occupy roles likely to gain from AI augmentation, like managerial and certain professional positions, which generally demand higher skills and experience accumulated over more extended periods. While these findings suggest that female and younger Singaporean workers are more likely to be in occupations with high AI exposure and low AI complementarity, it is also important to note that emerging research (Noy and Zhang, 2023; Peng et al., 2023; Brynjolfsson et al., 2023) indicates that generative AI may also complement inexperienced and lower-skilled workers in routine jobs such as writing, coding, and call center operations. These studies suggest that AI technologies might mitigate some displacement risks by enhancing worker productivity and capabilities in these roles. Additionally, the broad age categories used in this study limit the applicability of this analysis to a small share of young workers between 15 to 24 years old, who are typically students in casual or part-time jobs. Consequently, younger workers in prime-age full-time roles may experience different impacts from AI.





E. Policies

13. AI technologies offer the potential to boost productivity across sectors, but realizing these benefits requires the implementation of appropriate policies. As industries adapt to the rapid advancements in AI, policies focused on education and workforce training can equip individuals with the necessary skills to thrive in an AI-enhanced economy. Such re-skilling and upskilling programs are important even for workers in occupations that have high complementarity with AI, because high complementarity does not automatically imply that workers in those

occupations will see productivity increases or are immune to AI-induced displacement. For these workers to truly benefit from AI, relevant training and skills development are essential. In this regard, Singapore has existing frameworks, such as the *SkillsFuture* program and Career Conversion Programmes (CCPs), that provide training geared towards AI technologies and can be further enhanced. The analysis above highlights that a significant share of Singapore's workforce, particularly managers, science and engineering professionals and associate professionals, health and legal experts, and educators, could see productivity gains from AI, provided they receive the right training. Initiatives to raise awareness of the impact of key technologies such as AI on jobs and skills through Jobs Transformation Maps, along with efforts to encourage the adoption of AI to transform existing operations and processes, will position Singapore to better leverage the opportunities presented by AI. Furthermore, the government and the private sector can collaborate to identify emerging skills gaps and develop targeted training programs. By fostering a culture of continuous learning and innovation—which are also policy objectives set in the *Forward Singapore* initiative—Singapore can ensure its workforce remains competitive and adaptable in the face of technological change, setting a global standard for AI integration into the workforce.

14. Policies can also mitigate the disruptive impact of AI. Our analysis indicates that many in Singapore's workforce are in jobs with low AI complementarity, increasing their risk of being replaced by AI. This risk is particularly acute for those in clerical support, business and administration, and sales roles, making upskilling and reskilling programs critical for facilitating their transition to new employment opportunities. The planned introduction of a scheme offering temporary support for the involuntarily unemployed can mitigate the potential disruptive impact of AI on such workers. While the recently launched *SkillsFuture* Level-Up Program offers promising support, it predominantly targets mid-career individuals. Given our findings, expanding such initiative to include younger workers, who are at higher risk of displacement by AI advancements, can mitigate the impact of AI. Furthermore, incorporating AI literacy and digital skills training into the education system can proactively prepare future generations for the evolving job market, ensuring long-term resilience against the challenges posed by AI. Singapore's strong emphasis on human capital development, exemplified by initiatives like the National Digital Literacy Programme to improve digital literacy, equips its workforce with the necessary skills to thrive in an AI-driven economy.

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